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NLS Discussion Papers

Family Background and Labor Market Outcomes

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Thomas A. Dunn

June 1990

Report: NLS 92-13

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This final report was funded by the U.S. Department of Labor, Bureau of Labor Statistics under contract number J-9-J-7-0094. It was originally titled "Family Background, Labor Market Outcomes, and Race and Sex Differences in Youth Employment Outcomes." The authors have also acknowledged research support from the Center for Urban Affairs and Policy Research, Northwestern University. Avner Greif, Alex Idichandy, Michele Borsetti, Yasuyo Abe, and James Spletzer provided skillful research assistance. Opinions stated in this paper do not necessarily represent the official position or policy of the U.S. Department of Labor.

FINAL REPORT

FAMILY BACKGROUND AND LABOR MARKET OUTCOMES

Submitted by
Joseph G. Altonji*
Thomas A. Dunn

This project was funded by the U.S. Department of Labor Bureau of Labor Statistics under Contract Number J-9-J-7-0094. It was originally titled "Family Background, Labor Market Outcomes, and Race and Sex Differences in Youth Employment Outcomes." Opinions stated in this document do not necessarily represent the official position or policy of the U.S. Department of Labor. Reseach support from the Center for Urban Affairs and Policy Research, Northwestern University is also gratefully acknowledged. Avner Greif, Alex Idichandy, Michele Borsetti, Yasuyo Abe, and James Spletzer provided skillful research assistance.

*Principal Investigator

Family Background and Labor Market Outcomes

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Family Background and Labor Market Outcomes

EXECUTIVE SUMMARY

Objectives:

This report examines the links between the labor market experiences and economic outcomes of individuals who are related by blood or by marriage. Each chapter is an independent study. The main objectives of Chapter 1 are (1) to provide better estimates of inter and intragenerational correlations in family income and earnings, (2) to estimate earnings correlations among individuals who are related by marriage, (3) to examine intergenerational links among a broad set of labor market outcomes, and (4) to show how intergenerational labor market data can be used to examine the sources of labor supply variation, theories of labor turnover, and theories of wage structure. In Chapter 2 we attempt to identify the sources of variation and of family similarities in wages, hours, and earnings. In Chapter 3 we measure the extent to which the education and experience slopes of wage equations are influenced by IQ, parental education, and an index of family background variables, school characteristics, and personal characteristics that predict years of education completed.

Methodology

All three chapters are based upon matched inter and intragenerational panel data on siblings, their parents, and their spouses from the four original cohorts of the National Longitudinal Surveys of Labor Market Experience. We work with a wide variety of multivariate statistical methods and several different econometric models. In examining correlations among labor market outcomes we pay special attention to biases from transitory

variation and measurement error.

Findings

The results of our analysis of family links in economic outcomes in Chapter 1 are as follows. First, we find very strong intra and intergenerational correlations in family incomes. The sibling correlations are stronger for sisters than for brothers. Our preferred estimates are based upon a method of moments procedure that reduces bias from transitory variation. The correlations are .38 for brothers, .52 for sisters, and .56 for brothers and sisters, which are large relative to most estimates in the existing literature. The estimates of the intergenerational correlations of family income are .34 for son-father pairs, .46 for daughter-father pairs, .55 for daughter-mother pairs, and .54 for son-mother pairs. A regression analysis suggests that a one percent increase in the permanent family income of the parents raises the conditional mean of children's family income by .25 to .34 for sons and .32 to .42 for daughters. A substantial part of this effect operates through education and race.

Second, we find strong family links in earnings and in wages. Much of the effect of parental background on earnings and wage rates, particularly in the case of fathers and sons, operates through education and race.

Third, we find fairly strong correlations in the work hours of family members of the same sex. Our results suggest that family specific factors play an important role in hours determination.

Fourth, we find large covariances and correlations among the earnings of individuals who are related by marriage.

Fifth, we find that job turnover behavior is correlated among family members. We also show that young men whose fathers work in high wage

industries (controlling for human capital characteristics) tend themselves to work in high wage industries.

In Chapter 2 we present estimates of a factor model of earnings, hours and wages. We use the model to investigate the extent to which the parental and family characteristics that drive wage rates and work hours independently of wage rates are responsible for similarities among family members in labor market outcomes. We find that the wages of both sons and daughters are quite responsive to the permanent wage rates of fathers and mothers, with coefficients between .2 and .3 for our preferred specifications. The father's wage explains a substantially larger fraction of the total variance in wage rates, in part because the variation of the father's wage factor is substantially larger (by about one-third) than the variation in the mother's wage factor.

We also document that intergenerational correlations substantially overestimate the direct influence of fathers, and especially mothers, on wages. A substantial part of the relationship between a parent and child arises because assortive mating induces a substantial positive covariance in the wage rates of the parents.

We find that 6 percent of the total variance in young men's work hours is associated with parental preference factors and 17 percent is associated with an additional preference component that is common to siblings. For young women only about 9 percent of the total variance in hours is associated with parental <u>plus</u> sibling preference factors. The small influence of wage rates (particularly for young men, who have a low overall variation in hours), reflects the fact that our estimated labor supply elasticities are only .056 for young men and .184 for young women. For mature men only 3 percent of the

hours variance can be attributed to wage differences. On the other hand, wage differences explain 16 percent of the total variance in hours for mature women, who have a labor supply elasticity of .445.

We attribute 85 percent of the variation in the earnings of young men to wage rates and 15 percent to hours preferences. For mature men the figures are 97 percent and 3 percent. On the other hand, the hours preference factors account for 56 percent of the variance in the earnings of young women. For the mothers, 71 percent of the earnings variance is due to the wage factor, and 29 percent to the hours preference factor. Consequently, our decompositions of the earnings variances differ by gender, and by age in the case of women.

In our analysis of education and experience slopes (Chapter 3) we find that IQ, father's education, mother's education, and an index of family background, secondary school characteristics, and personal characteristics that predict years of schooling completed have only weak influences on the relationship between education and wages, and between labor market experience and wages. In a number of cases, the family background interactions work in the wrong direction or are statistically insignificant. In view of the results, it seems unlikely to us that the effect of family background on the education slope of wages is responsible for more than a small part of the powerful effect of family background on years of school completed.

Implications

Our results imply that characteristics common to family members have a very important effect on the distribution of income and wages, and also play an important role in other aspects of labor market behavior, including work hours and job turnover. The findings of strong links between individuals who

are related by marriage are particularly interesting. We believe that extending the factor model in Chapter 2 to include equations for spouse's earnings, hours and wages should be a high research priority. Finally, we are surprised that we do not find much of an effect of family background and IQ on the payoff to education and experience and plan to continue our analysis using other data sets.

Chapter 1

Relationships Among the Family Incomes and Labor Market Outcomes of Relatives

Joseph G. Altonji

Thomas A. Dunn

Introduction

This chapter quantifies the links between the labor market experiences and economic outcomes of individuals who are related by blood or by marriage using panel data on siblings, their parents, and their spouses from the four original cohorts of the National Longitudinal Surveys of Labor Market Experience. Our main objectives are (1) to provide better estimates of inter and intragenerational correlations in family income and earnings, (2) to estimate earnings correlations among individuals who are related by marriage, (3) to examine intergenerational links among a broad set of labor market outcomes, and (4) to show how intergenerational labor market data can be used to examine the sources of labor supply variation, theories of labor turnover, and theories of wage structure.

The first purpose of the paper is simply to provide better estimates of the correlations of permanent income and earnings levels between parents and children and among siblings. Many studies have examined sibling correlations, and a small number have examined intergenerational family income

correlations in the U.S.[1] As Solon (1987, 1989) points out, previous U.S. studies finding weak intergenerational correlations (see Becker and Tomes (1986)) are plagued by homogeneous samples and lack of attention to downward biases caused by measurement error and transitory variation in income or earnings observations drawn from a single year.[2] We use the NLS data, which is a broad based sample, and compute correlations using two alternative approaches that should be less sensitive to transitory variations in the data. The first is a method of moments estimator that is constructed to be insensitive to transitory variation. The second approach uses time averages of the data for individuals. We also use an instrumental variables estimator to estimate the regression coefficient relating the permanent components of parents' income, earnings, wage rates and other labor market variables to those of their sons and daughters.[3]

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1. See Becker and Tomes (1986) for references. Solon (1987, 1989) provides a critique of the previous intergenerational studies and provides new evidence based on the PSID. His results are discussed below. Bielby and Hauser (1981) use CPS data to analyze the relationship between son's earnings and the son's report of parental income and attempt to correct for biases that arise from response error. They obtain a correlation of .161. (See their Table 8.) Other prominent references in the literature include Brittain (1977), Griliches (1979), Solon et al (1987), Corcoran and Jencks (1979), Kearl and Pope (1986), and Olneck (1977), Behrman and Taubman (1985) and Taubman (1977).

2. Becker and Tomes mention the problems of measurement error and transitory variation in income, and several of the studies they cite use time averages to try to reduce the problem. The problems posed by homogenous samples are not well known, although Corcoran and Jencks (Chapter 3, Section 1) mention it in the context of studies of sibling correlations.

3. Why focus on the correlation in permanent income rather than total income? The answer is that we view the inequality of lifetime income rather than inequality of income in a given year as the key variable of interest, and transitory variation in income that is weakly correlated across years has little effect on the cross sectional variance in income over a lifetime. Consider the case in which income in a given year for a particular person is the sum of a fixed or permanent component and a serial uncorrelated transitory component. Suppose that the variance in the transitory component is twice as

The second purpose of this chapter is to provide evidence on the correlations in earnings among those individuals who are related by marriage. Specifically, we present evidence on covariances and correlations between the labor market outcomes of husbands and wives, fathers and sons-in-law, mothers and sons-in-law, brothers-in-law, etc. While a number of researchers have examined the role of assortative mating patterns in marriage in the

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large as the variance of the permanent component. Then the contribution of the permanent component to the cross sectional variance in the undiscounted sum of income over a 40 year period is [1600/(40*2)] or 20 times larger than the contribution of the transitory component. Discounting increases the relative importance of the transitory component, but for realistic interest rates, the permanent component dominates the income variance. The relative importance of transitory factors does increase if they are correlated over time. However, even if the transitory components were a series of disturbances that took on the same value for four years, then the contribution of the permanent component would be [1600/(4*4*10*2)] or 5 times larger than the contribution of the transitory components.

It should be pointed out that the term "permanent" component is used in the paper to refer to a component that is fixed over time for a given individual. In fact, it is more realistic to consider income as the result of an initial condition that remains fixed, a random walk component that accumulates over time, and a transitory component that is uncorrelated across periods of more than a year or two. In this circumstance parental income and earnings in a given year reflect not only their earnings capacity at the time they entered the labor market but also the accumulated effect of changes in fortune that have occurred over many years, some of which may have occurred long after their children left the household. Our estimates of the variance of parental income will reflect not only the variance of initial parental income but also the variance of the accumulated random walk component. (Note that below we report that the variances of father's family income, earnings, and wage rates are larger than the corresponding values for sons.)

Our estimates of the covariance between parents and children will reflect covariances of the child's income with the parents' fixed income component and with the parents' random walk component. Assuming that most of the intergenerational correlation is in the fixed components of income rather than in the stochastic variation that occurs after entry in the labor market, then the correlation between parents' income at age 50 and children's income at age 30 may be greater (less than) than the correlation between parents' income at age 50 (30) and children's income at age 50 (30). This is because as the child and parents age, the importance of the child's and the parents' random walk components of income increase, lowering the correlation coefficient. In future work, it would interesting to estimate family correlations in discounted lifetime income using a statistical model of income that allows for random walk components and serially uncorrelated components.

determination of inequality, we do not know of any previous studies that have examined the relationships between parental and sibling earnings and the earnings of spouses.[4] We produce a set of correlation matrices relating the labor market outcomes of individuals who are related by blood or by marriage that can be used by other researchers. The covariances and correlations are quite large in many cases.

The third purpose is to examine family relationships among a broad set of labor market outcomes. While a large number of studies have examined intra and intergenerational links in family income or occupational status, few have attempted to examine family links in the main components that influence earnings. Is the link between the economic success of fathers and sons primarily due to work effort or to wage levels? Is the propensity to change jobs a personal characteristic that is correlated among family members?

The fact that little is known about intergenerational links in unemployment experience, work hours, labor turnover, or the rate of return to education is one motivation for our examination of these topics in this report.[5] Additionally, we show how evidence on the relationships among labor

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4. Behrman and Taubman (1989) report education correlations for a variety family relationships, including sisters-in-law. Blau and Duncan (1967) analyze evidence from "Occupational Changes in a Generation" (OCG) indicating that there is a substantial correlation between the occupational status of fathers-in-law and sons-in-law and between fathers-in-law.

5. The gap in our knowledge is due in part to the fact that analysis of these questions requires detailed panel data for a representative sample on the labor market experience of mothers and fathers and sons and daughters. Until recently, the necessary data have been unavailable. Altonji (1988) and Corcoran et al (1989) are among the few studies that provide data that can be used to address the question of whether the strong relationship between an individual's income and that of his parents is due to common work effort, to hours worked, to unemployment experiences, to common wage levels at the time of entry into the labor market, or to common returns to education and experience.

market outcomes of family members may be used to address broader questions about labor supply, turnover behavior, and even the industry structure of wages that are normally studied using cross sectional data on unrelated individuals.

One obvious application is to labor supply determination. Economists have not been very successful in explaining hours differences among males using wage rates, nonlabor income, and observed personal characteristics. (See, for example, Pencavel's (1986) survey.) It is possible that hours choices are influenced by differences in preferences that are hard to measure but depend upon genetic and environmental factors that are correlated among family members. Indeed, it is common to say that an individual is from a "hard working family." While ultimately we would like to have a structural model of the determinants of labor supply preferences, it is useful to start by examining whether or not a common family component plays an important role in hours determination. In this chapter we present descriptive evidence on hours links, and in Chapter 2 we use a factor model to measure the importance of parental and sibling preference factors in the variance of hours worked and of earnings for young men and young women. We find preferences play a large role in hours linkages.

This chapter proceeds as follows. In section I we discuss the NLS data used in the study. In section II we discuss the statistical methods used in the paper. In section III we quantify the links among family members in family income, earnings, hourly wage rates, and work hours. We also present evidence on links among individuals who are related by marriage. In section IV we present evidence on the relationship between the turnover behavior of pairs of related family members. We also discuss the implications of these

relationships for studies of the role of individual heterogeneity and job match heterogeneity in the turnover process. In section V we show that young men whose fathers work in high wage industries (controlling for human capital characteristics) tend themselves to work in high wage industries. We argue that the results are consistent with nonmarket clearing explanations for industry wage premiums (such as efficiency wages) only if family connections play a key role in gaining access to high wage firms. Section VI concludes the chapter.

I. Data

The data used in this report are from the four Original Cohorts of the National Longitudinal Surveys of Labor Market Experience. Specifically, we work with the sample of Young Men who were 14 to 24 years old in 1966 and were followed through 1981, the samples of Young Women who were 14 to 24 in 1968 and Mature Women who were 30 to 44 in 1967 and continue to be followed, and the sample of Older Men who were 45 to 59 years old in 1966 and were last surveyed in 1983. We use data through 1982 in the case of the young women and through 1984 in the case of mature women. Some of the households contributed more than one person to the young men and young women surveys, and in some cases the households contributed to both the youth surveys and older men and mature women surveys. Consequently, it is possible to match data on sibling pairs and parent-child pairs. For some of our analysis, we have also matched data on husbands and wives who were members of the older men's and mature women's surveys. The bottom rows of Tables 1 and 2 summarize information on the sample sizes of the original cohorts, the numbers of brother, sister, and brother-sister pairs, and the number of parent-child pairs. It is important

to emphasize that the sample sizes used in the analyses vary depending upon the particular variables being considered and the number of family member matches that are available.

Because sample members are asked questions about the labor market outcomes of their spouses, we are also able to examine the relationships among the labor market outcomes of individuals who are related by marriage. For example, we report the covariance of earnings of fathers and sons-in-law using the reports of spouse's earnings provided by members of the young women's cohort who could be matched to their fathers.

Many of our analyses exploit the availability of panel data on the individuals in the sample. However, data on a particular question may be missing either because the individual left the sample prior to that survey or because the response is missing or invalid for other reasons. In the case of the young men and young women our basic approach is to restrict the sample to individuals who were at least 24 years old prior to leaving the survey. We chose this age cutoff to reduce transitory variation in labor market outcomes associated with the transition between school and work. We use labor market data (wages, hours, unemployment, etc.) from a particular year only if the individual was at least 24 and was out of school and did not return to school in a subsequent year.

The fact that many of the older men in the sample approach retirement age during the course of the survey raises additional complications. Earnings, work hours, and wage rates of such individuals after retirement may not be closely related to the typical or "permanent" values for these individuals over the course of their careers. To minimize this problem, we only use data on family income and labor market variables for individuals who had not yet

retired, and who were less than 61 years old when the data was collected. Since the age in 1966 of the older men ranges from 45 to 59, there is substantial variance across sample members in the number of years of labor market data available.[6] Retirement is not a concern for the mature women's

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6. There is always a concern in an analysis of sibling or intergenerational data that the very fact that it was possible to collect data on several family members makes the data unrepresentative. For example, it is necessary for more than one sibling to remain in our sample past the age of 24 in order for the sibling pair to contribute to our analysis. In the case of the NLS, two special problems come to mind. First, both the father and the child must satisfy the age restrictions of the sample design in the base year of the survey. Since a substantial number of children leave the household by age 24, one might expect that the matched sample would over-represent individuals who are still living with their parents when they are in their early twenties. This problem is mitigated to some extent by the fact that the young men in the father-son sample are about .7 years younger than the young men's sample as a whole which had an average age of 18.1 years in 1966. The corresponding numbers for daughters are .5 and 16.7 years.

We have computed summary statistics for the matched parent-child samples and compared them to the corresponding full cohort samples. (A thorough job of this would require a full paper.) The older men in the father-son sample are about 1 year younger than the sample average for the entire older men cohort. The fathers who could be matched to children of either sex have somewhat higher family income (16%), earnings (7%), wages (6%), hours worked per week (2%), and hours worked per year (4%). They also have .33 more years of education than the mature men's sample as a whole. (These differences might reflect differences between older men who had children and older men who did not.)

The mature women in the matched samples are about 2 years older than the sample of all mature women and have family income, earnings, wages, hours worked per week, and annual hours worked which are lower by 5.1%, 17.4%, 9.4%, 1%, and 3%. They also have .70 fewer years of education than the sample of all mature women (10.3 versus 11.0 years).

As noted above, the young men matched to fathers are almost three quarters of year younger than the sample of all young men, but they have higher family incomes (6.2%) and about .5 additional years of education. Earnings, wages, and hours worked per week are equal for the two groups, while annual hours worked are lower by 3.5% for the young men matched to fathers. Young men who are matched to mothers are about two years younger than the entire sample of young men and have somewhat lower family incomes, earnings, wages, and annual hours. Education is similar for the two groups. The young women follow the same general pattern as the young men. Those whose fathers are in the mature men cohort are somewhat younger, better educated (by .5 years), and more successful than the young women's cohort as a whole. Young women matched to mothers are one and a half years younger than young wome.. as a whole and have somewhat lower family income (by 7.7%). Average education (at 12.5 years), wages, earnings, and hours worked for the young women in the

sample through the years we study.

For all four cohorts we excluded wage observations of less than $.40 per hour, earnings of less than $100 per year, and family income of less than $200 per year (all in 1967 dollars). Also only annual hours (constructed as reported number of weeks worked times reported number of hours worked per week) greater than zero and less than 5000 hours were counted.

In part of the analysis we work with the log of number of weeks of unemployed for those who have positive weeks of unemployment in a given year. A problem with this weeks of unemployment measure is that determinants of the incidence and the duration of unemployment spells are related, and unfortunately, by taking logs, we have excluded all observations on zero weeks of unemployment. In retrospect, it would have been better to work with the level of weeks of unemployment, and we intend to re-work the analysis of unemployment in the future.

In the paper we work with two job turnover measures. For a young man, the variable, NNUMEMP, is the number of employers the individual reports from 1966 until either 1981 or the year that he left the sample. This variable counts multiple spells with the same employer only once. The variable NTURNOV is the number of job changes the individual reports over the same period. We emphasize the results for NNUMEMP is the text, although the results based on

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mother-daughter sample are the same as for the full sample of young women.

With regard to sibling pair analysis, the sample restrictions may imply that we are looking at siblings who are somewhat closer in age and from somewhat larger families than would the case from a representative sample. However, we suspect that this problem is minor given that the initial age range is 14 to 24 years.

NTURNOV are usually very similar.[7] The corresponding variables for young women cover the years 1968 to 1982 or the year the women left the sample. The intervals are 1967 to 1984 for mature women, and 1966 to 1983 for older men. For older men, we do not accumulate employer changes or job changes after the individual reaches age 61 or retires. There are a few problems with these turnover measures, not the least of which is that they are affected by the year in which the person left the sample and by his or her labor force participation history. (We discuss additional problems below.) We view these two measures as only rough indicators of turnover rates.

II. Overview of Econometric Models and Methods

In this section we begin by discussing the covariances and correlations among a variety of labor market outcomes for family members. Our aim is to estimate the correlations among the permanent component of the labor market outcomes of family members, and so it is necessary to compute the correlations using an approach that reduces the downward bias introduced by transitory variation and measurement error. We implement two different estimation procedures.

The first approach, which we will refer to as the time average approach, computes the covariances and the correlations among the time averages of the labor market outcomes of matched family members. We use all of the available data on each individual that meets the criteria discussed above to compute the time average for the individual. The sample used to compute the brother correlations consists of all unique brother pairs for whom valid data are

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7. In the text and appendix tables which follow, variable names beginning with the letter N refer to young men (B to brothers), G to young women (S to sisters), M to older men, and W to mature women.

available for the particular labor market outcome. The samples for the other family relationships also consist of the unique pairs of individuals who are in that relationship. For example, a family with three brothers who have valid data on a particular labor market variable will contribute three observations to the sample used to compute the brother pair covariances. A family contributing one father and three daughters to the NLS older men and young women cohorts will contribute three observations to the father-daughter sample, and three to the sisters sample.

The second approach, which we refer to as the method of moments approach, is to compute family covariances of a particular labor market outcome by first adjusting the data to have zero mean, computing the unique set of crossproducts of the elements of the vector of labor market outcomes in different years for one family member with the elements of the vector of labor market outcomes of the other family member, and taking the mean of all the crossproducts for all of the pairs of family members. We estimate the variance of the permanent component of labor market outcomes for young men by first computing the crossproducts of all unique pairs of yearly observations on a labor market outcome that are for the same individual and that are separated by more than two years in time and then taking the average of all of the crossproducts for all individuals.[8] We do the same for young women's,

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[8]. If a labor market variable such as the wage rate is equal to a fixed component and a transitory component that can be represented by a moving average process of order 2 or less, then the transitory component will not bias our variance estimates. Abowd and Card (1989) develop a three components-of-variance model to describe the covariances of hours changes and earnings changes for adult males in the NLS, the PSID and the SIME/DIME data sets. The components are as follows: a stationary serially uncorrelated measurement error, a shared component of hours and earnings which follows a non-stationary MA(2) process, and a time-varying component which affects only the variances of earnings and hours and their contemporaneous covariance. They show that such a representation fits the estimated covariances of hours

mature women's, and older men's variables.

The specific formula for the covariances, variances, and correlations are as follows. Let $Y_{ik(j)t}$ be the adjusted[9] labor market outcome of an individual, where i denotes a set of related individuals, k is the type of individual (e.g., young man, young woman, older man, or mature woman) and j is an index indicating the specific individual of type k from family i. (The index j may exceed 1 when k refers to young men or young women and there is more than one young man or young woman from a given family.) Then the method of moments estimator of the covariance of variable Y across the family pairs of type k,k' is

$$(1) \quad Cov(Y_{ik},Y_{ik'}) = \sum_i \Big(\sum_j \sum_{j'} \sum_t \sum_{t'} Y_{ik(j)t}\, Y_{ik'(j')t'}\Big) / N_{YYkk'}$$

When k= k', as is the case for brother pairs and for sister pairs, then the covariance estimator is

$$(2) \quad Cov(Y_{ik},Y_{ik}) = \sum_i \Big(\sum_j \sum_{j' \geq j} \sum_t \sum_{t'} Y_{ik(j)t}\, Y_{ik(j')t'}\Big) / N_{YYkk}$$

The method of moments variance estimator for the variable Y for the person of type k is

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and earnings quite well. They find in all three data sets that changes in the experience- adjusted log earnings and log hours are uncorrelated with their own lagged changes at more than two periods. Since differencing increases the order of an MA term by 1, their results indicate that the MA error component in the level of earnings and hours is of order less than 2.

9. We work with the residuals of a regression of each of the labor market outcomes against a cubic in age and a set of year dummies. Note the time averages used in the time average approach are not adjusted for the individual's age nor for the year from which the data are drawn. In retrospect, we wish that we had made this adjustment, but doubt that it would make much difference; see footnote 33 for supporting evidence.

$$(3)\quad Var(Y_{ik}) = \sum_i \Big(\sum_j \sum_t \sum_{t'>t+2} Y_{ik(j)t}\, Y_{ik(j)t'}\Big) / N_{Yk}$$

In the above equations $N_{YYkk'}$, $N_{YYkk'}$ and N_{Yk} are the number of terms in the sums taken in (1), (2), and (3), respectively.

The correlation coefficient for the family pairs of type kk', k≠k' is

$$(4)\quad Corr(Y_{ik}, Y_{ik'}) = Cov(Y_{ik}, Y_{ik'}) / [Var(Y_{ik}) * Var(Y_{ik'})]^{.5}$$

The correlation coefficient for family pairs of type kk (i.e , brother-brother or sister-sister) is

$$(5)\quad Corr(Y_{ik}, Y_{ik}) = Cov(Y_{ik}, Y_{ik}) / [Var(Y_{ik})].$$

Note that we use the full samples of young men, young women, older men, and mature women to compute the variances $Var(Y_{ik})$ for each type.

We prefer the correlation estimates based upon the method of moments approach because we believe that the method of moments estimates of the variance for each type of family member are less likely to suffer from downward bias due to transitory variation in labor market outcomes and measurement error than the variance estimates based on the time averages. However, the method of moments estimator may be more sensitive to heterogeneity in variances and covariances of the labor market outcomes that is related to (a) whether or not particular individuals have a relative in the sample, and to (b) the number of years of data on a particular family member. The estimates of the covariances based upon the time averages give each pair of individuals the same weight, while the estimates based upon unique pairs of observations across individuals and over time (that is, the method of moments estimators) give proportionately more weight to pairs of individuals who

contribute many time series observations. In most cases, the covariance estimated by (1) and (2) are reasonably close to the covariances calculated using the corresponding time average estimators. (If the expected value of the covariance is unrelated to the amount of valid labor market data available, then the method of moments estimator is more efficient.) In most cases, the estimates of the correlations are larger using the method of moments estimation procedure than the time average procedure; the difference is almost always due to somewhat lower estimates of the variances of the labor market outcome (the denominator in (4) or (5)), rather than higher estimates of the covariances.

Regression Equations

Regression equations relating the labor market outcomes of children to those of their parents provide a second way of summarizing family relationships in labor market outcomes. Since it is easy to incorporate control variables into the analysis, this approach provides a convenient way to assess the extent to which the links among family members are due to particular factors, such as education, race, or location. For example, part of the positive correlation between the separation rates of fathers and sons may be due to correlation between the educational levels of fathers and sons.

Here we estimate equations of the following form:

$$(6a)\quad WAGE_{is} = A_1 X_{is} + A_2 X_{if} + \gamma_{sf} WAGE_{if} + e_{is}$$

$$(6b)\quad WAGE_{id} = B_1 X_{id} + B_2 X_{if} + \gamma_{df} WAGE_{if} + e_{id}$$

$$(6c)\quad WAGE_{is} = C_1 X_{is} + C_2 X_{im} + \gamma_{sm} WAGE_{im} + \epsilon_{is}$$

$$(6d)\quad WAGE_{id} = D_1 X_{id} + D_2 X_{im} + \gamma_{dm} WAGE_{im} + \epsilon_{id}$$

In the above equations $WAGE_{ik}$ is the time average of the log wage rate and X_{ik} are personal characteristics, where k= d in the case of young women, s for young men, f for fathers and m for mothers. The key parameters of interest are γ_{df}, γ_{dm}, γ_{sf}, and γ_{sm}, which reflect the effect of a one unit change in the parent's outcome on the labor market outcome of the son or daughter. In the empirical work we estimate similar equations for log earnings, log family income, log annual hours, and other labor market variables.

We use two estimation methods. The first is ordinary least squares. The problem with OLS is that transitory variation and measurement error in particular years may affect the time average of the labor market variable. This is likely to lead to downward bias in the γ estimates. As an alternative, we use an instrumental variables procedure. Specifically, we put the first observation on $WAGE_{ikt}$ into the equation in place of the wage mean, $WAGE_{ik}$, where k= m or f. The variable $WAGE_{ikt}$ will equal the permanent component of the wage of parent ik plus a transitory component. We then compute $WAGE_{ik(t)}$, the mean of the parent's wage observation over t <u>excluding</u> the first observation from the computation. The mean, $WAGE_{ik(t)}$ will be correlated with the permanent component of $WAGE_{ikt}$, and it will be uncorrelated with the transitory component if the transitory component is white noise. Consequently, under the white noise assumption we may estimate the response of $WAGE_{id}$ (or $WAGE_{is}$) to the permanent component of $WAGE_{ikt}$ by using $WAGE_{ik(t)}$, X_{id} (or X_{is}) and X_{ik} as instrumental variables for $WAGE_{ikt}$, for k= f or m.

We now turn to estimates of the correlations, covariances, and

regression coefficients relating the labor market outcomes of relatives.

III. Intra- and Intergenerational Links in Family Income, Wage Rates, Earnings, and Work Hours

In this section we present the estimates of the covariances and correlations among log family income, log earnings, the log hourly wage rate, and log work hours for family member pairs. In section III.1 we discuss the results for family income. In section III.2 we discuss earnings, wages and work hours. In section III.3 we briefly discuss the correlations among the earnings of "in-laws." In the remainder of this introduction we provide a few general comments.

Appendix Tables A1- A21 present the correlations among the time averages of selected labor market variables for various family member pairs. In the text we emphasize the covariances and correlations across family member pairs of the same labor market variables and ignore the off-diagonal terms which appear in the Appendix tables. The results are summarized in Table 1. The column headings report the type of family relationship. The row heading reports the labor market variable involved. For example, we find that correlation of the mean of log family income among brothers is .27. The correlation in the number of employers they have had is .16. The correlation in family income and log earnings between sons and fathers are .27 and .22, respectively. The number of observations used to compute a given correlation depends upon the labor market variable under consideration and the number of family member matches for the particular relationship. Beneath each correlation we report the number of sample observations. (At the foot of each column we report the number of unique family pairs for each type of

family relationship.[10]) In Table 2 we present the means, variances and number of observations on the various labor market outcomes for the full samples of young men, young women, older men, and mature women in the four NLS cohorts.[11]

Table 3 provides estimated family covariances and correlations based on the method of moments procedure for log family income, log earnings, log wage rates, and the log of annual work hours, while Table 4 presents the estimated method of moments variances for various labor market outcomes for each of the four cohorts. Appendix Tables A22- A25 provide the full covariance matrices of labor market outcomes produced by the method of moments estimators.

We present evidence on both the covariances and correlations because the correlations depend on both the covariance of the common component of the labor market outcome and the variances of the components affecting only the individuals, while the covariance does not depend on the individual specific variance components. It is important to keep this in mind when assessing the relative strength of the different family relationships for a particular labor market outcome. For example, although the correlation in the family incomes is .27 for brother pairs and .20 for brother-sister pairs, the covariance of log family income is exactly the same for the two sibling pair types. The smaller correlation between brothers and sisters reflects a larger variance of log family income for young women.

In addition to the covariances and the correlations, we report estimates of the regression equations (6) in Tables 5a- 5d. These indicate the

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10. The reported figure is the number of potential matches before the cohorts were screened for minimum age, completed schooling, and retirement.

11. In each of the Appendix tables, we present the means and standard deviations of the variables for the subsample of matched family members who are used to compute correlations and covariances shown in the particular table.

association between a unit change in the parent's labor market outcome and the change in the expected value of the son's or daughter's outcome.

III.1 Family Income

The first row of Table 1 provides time average estimates of log family income covariances and correlations for various pairs of family members. The sibling correlations are .27 for brothers, .37 for sisters, and .20 for brothers and sisters. The covariance of sisters' family incomes is more than double the covariance between brothers'. The effect of the higher covariance on the family income correlation is partially offset by the fact that among the set of young men and women who are independent of their parents, the variance of log family income is much larger for young women.[12] It is interesting to speculate on whether this higher variance is a reflection of the large number of female headed households with children.

The method of moments estimates imply substantially higher sibling correlations in family income. The correlations are .38 for brothers, .52 for sisters, and .56 for brothers and sisters. We view the estimates for sisters and for brother-sister pairs as very large relative to those in the existing literature. The estimate for brothers is in the same range as Solon et al's (1987) estimate of .342, however their estimate for sisters' earnings is much smaller at .276. (See footnote 22 for further comparisons.)

The intergenerational correlations of family income based upon the time averages are .27 for sons and fathers, .31 for daughters and fathers, .30 for daughters and mothers, and .31 for sons and mothers. However, the method of

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12. Note that the covariance between brothers and sisters is about the same as the covariance between brothers, even though the correlation is .27 for brother pairs and .20 for brother-sister pairs.

moments estimates are .34 for son-father pairs, .46 for daughter-father pairs, .55 for daughter-mother pairs, and .54 for son-mother pairs. Our results based on the time averages are on the low end of those reported by Solon (1989) and by Altonji (1988) who use data on fathers and sons from the Panel Study of Income Dynamics.[13] At the same time, the method of moments estimates for all intergenerational pairs except son-father are higher than any previous estimates for the U.S. in the literature.[14]

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13. Solon runs OLS regressions of the son's earnings in 1984 on various constructions of the father's earnings variable, and age controls. Using a single year measure of father's earnings, the father's variable coefficient ranges from .247 to .386, depending on the year of the father's report. When a five year average of father's earnings is used, its coefficient is .413. In an equation with son's 1984 log wage as the dependent variable, father's log wage in 1967 appears with a coefficient of .294; in an analogously constructed family income equation, father's log family income in 1967 enters with a coefficient of .483.

Altonji works with the time average of the level rather than the log of family income and obtains a correlation of .37 between fathers and sons.

14. Solon also presents a set of estimates in which the intergenerational correlation is estimated from an instrumental variables estimate of the relationship between son's income in 1984 and father's income in 1967, using father's education as an instrument for father's income to reduce the effects of transitory variation in income. He obtains a regression coefficient of .530. For similarly constructed equations for wages and earnings, the IV coefficients are .449 and .526, respectively. However, he points out that the regression coefficient is an estimate of the intergenerational correlation coefficient only if the variances of the family income of father and son are equal. (As we have noted, this comment also applies to our OLS and IV estimates of equations (6).) Second, he argues that this estimate is likely to be upwardly biased even if the family income variances are equal because father's education should probably appear itself as an independent variable in the son's family income equation.

When we repeat this IV estimation technique with son's log family income in 1981 as the dependent variable using father's reported education and age controls as instruments for his mean log family income, we find a coefficient of .352 on the father's variable. (Our corresponding OLS coefficient is .268.) For log wages, we find an IV coefficient of .421 (and an OLS coefficient of .297) on father's mean log wages; for log earnings, the IV coefficient is .411 (and the OLS coefficient is .255) on father's mean log earnings. In summary, our estimated IV coefficients are smaller than Solon's for the intergenerational income, earnings, and wage equations.

Regression Results for Family Income

Tables 5a, 5b, 5c, and 5d report OLS and IV estimates of the regression equations (6a) through (6d) relating the labor market outcomes of fathers and sons, fathers and daughters, mothers and sons, and mothers and daughters (respectively). We report results for two sets of control variables. Control set I consists only of the child's age in 1966 (1968 for young women), age squared, and age cubed, and the parent's age in 1966, age squared and age cubed. Control set II consists of control set I plus controls for the child's race, residence in the South, residence in an SMSA, a cubic in the child's education, and a cubic in parent's education. To save space, we focus on the IV estimates in the text. We wish to emphasize that since the variances of family income are higher for fathers and mothers than for sons and daughters, the regression coefficient estimates are likely to be smaller than the correlation coefficients even when no controls are added. This is especially true for fathers and sons.[15]

Using control set I, the coefficients on father's family income is .249 for sons and .322 for daughters. Since the variables are in logs, the result for family income implies that the elasticity of son's income with respect to father's income is .249. For sons, much of the relationship in incomes appears to operate through education and, to a lesser extent, race. To see this, note first that when we use control set II, we obtain .073 as the coefficient on father's family income. By adding the son's race, father's education, and son's education one at time to control set I, we have

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15. When control variables are excluded, the probability limit of the correlation coefficient is equal to the probability of the regression coefficient times the probability limit of the standard deviation of the father's outcome variable divided by the standard deviation of the son's outcome variable.

determined that including the son's education as a regressor has the largest negative impact on the magnitude of the father's family income coefficient, which is what we would have expected a priori.[16]

The estimates of the relationship between family income of the mother and family income of sons and daughters are typically stronger than the corresponding results for the father-son and father-daughter samples. The IV estimate for mother-son pairs with controls for their ages only (control set I) is .340. The estimate for mother-daughter pairs is .422. The estimates for mother-son and mother-daughter pairs fall to .163 and .152 (respectively) when control set II is used.

Since in the case of two parent households the family income of mothers and fathers is the same, the larger estimates when using the mother-daughter and mother-son samples merit some discussion. We suspect that the difference in father-child and mother-child regression coefficients arises for two reasons. First, because of the design of the NLS, the parent's family income data in the father-son and father-daughter sample is obtained when the father is somewhat older than in the mother-son and mother-daughter sample. To the extent that family income is subject to permanent shifts that occur after children leave the household, then parental income in later years may have a weaker relationship with children's permanent income.[17] Second, the mother-

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16. When one adds only race to control variable set I as regressors in the IV equations for family income, earnings, and wages one obtains coefficients on the father's variables of .217, .153, and .244, respectively. Adding father's education (with race excluded) leads to IV estimates of .227, .166, and .278. Adding only son's education to control set I leads to smaller IV coefficients on the father's variables: .136, .092, and .197.

17. See footnote 3. A number of studies, such as MaCurdy (1982) and Altonji et al (1986), provide evidence that family income and earnings are subject to highly persistent shocks.

son and mother-daughter samples obviously include female headed, single parent families, while the father-son and father-daughter samples do not. It is possible that family income has larger effects in the case of single parent families than two parent families.[18] We suspect that estimates based on the father-son and father-daughter samples understate intergenerational links in family income.[19]

In summary, we find very strong intra and intergenerational correlations in family incomes. The sibling correlations are stronger for sisters than for brothers. The regression analysis suggests that a one percent increase in the permanent family income of the parents raises the conditional mean of children's family income by .25 to .34 for sons and .32 to .42 for daughters. A substantial part of this effect operates through education and race.

III.2 Earnings, Wage Rates, and Work Hours

When we use time averages, the estimated correlations of log earnings are .28 for brothers, .23 for sisters, and only .08 for brother-sister pairs. However, we obtain corresponding estimates of .35, .26, and .29 when we use

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18. We plan to investigate this hypothesis by including an indicator for "female-headed household" interacted with the mother's family income measure in the family income equations for the matched mother-son and mother-daughter data sets, and observing whether the link in incomes is sensitive to the presence of the father in the household.

19. Altonji (1988) uses a small sample of father-son pairs from the PSID to estimate separate regressions for son's average values (over the years in which he works positive hours) of annual work hours, annual hours of unemployment, the log of the real hourly wage rate, the log of real earnings, and the job separation probability against the corresponding variable for the father and controls for the son's education, experience and race, and the father's education and experience. His results show that virtually all of the father's labor market variables have a strong positive association with the corresponding labor market variable of the son. His results also suggest that race and father's education have independent influences on the labor market outcomes.

the method of moments procedure to isolate the correlation of the permanent components of earnings. The intergenerational correlation coefficients for earnings are also sensitive to the estimation method. We prefer the estimates based on the method of moments procedure, which are .39 for fathers and sons, .29 for mothers and sons, .40 for fathers and daughters, and .27 for mothers and daughters.[20] The method of moments estimates of the earnings correlation between fathers and sons are large relative to the estimates summarized in Becker and Tomes (1986) but are comparable to the results of Solon (1989) using the PSID.

It is interesting to look separately at the components of earnings: hourly wage rates and annual hours. Using the method of moments approach we obtain log wage correlations of .42 for brothers, .39 for sisters, .41 for brother-sister pairs, .41 father-son pairs, .38 for father-daughter pairs, .36 for mother-son pairs, and .35 for mother-daughter pairs. (The corresponding estimates based on time averages are typically slightly smaller.) Thus, we find somewhat stronger family relationships in log wages than in log earnings.

Given this fact and the fact that earnings depend upon work hours as well as upon wages, it is not surprising that the correlations in annual hours are usually smaller than the correlations in wages. However, the method of moments estimates are substantial in all cases involving family members of the same sex. For example, the annual hours correlation is .34 for brothers, .28

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20. A comparison of the covariances reported in Tables 1 and 3 and the variance estimates reported in Tables 2 and 4 suggests that in most cases the larger correlations obtained with method of moments procedure result from smaller estimates of the variances for family member type rather than larger estimates of the covariances across family members of the various labor market outcomes.

for sisters, .23 for fathers and sons, and .24 for mothers and daughters.[21,22] The large correlations between brothers and between fathers and sons are particularly striking in light of the fact that hundreds of studies of male labor supply have examined the effects of family characteristics, wages and income on hours worked and have met with little success in explaining hours worked for males.[23] (See Killingsworth (1983) and Pencavel (1986) for surveys of the literature.) The findings in Table 3 suggest that factors common to family members explain a substantial part of the permanent variation in work hours among males. In Chapter 2 of this report, we show that the similarity in the wage rates of brothers plays only a small role in the similarity in their hours worked.

Part of the relationship in annual hours, then, may be due to correlation

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21. The lower correlation for sisters masks the fact that the covariance in hours is much larger for sister pairs than brother pairs.

22. Solon et al (1987), using data from the PSID and analysis of variance estimators, find the correlations of brothers' log earnings, log annual hours, and log wages to be .448, .410, and .534; all are larger than our corresponding method of moments estimates which were .35, .34, and .42. Corcoran and Jencks (1979) provide estimates from several survey data sets and pick .17 as the best available point estimate of the earnings correlation between brothers. They pick .12 as a minimum estimate and .28 as the maximum. We believe their estimates are biased downward as a result of an inadequate correction for measurement error and transitory earnings components.

23. Table 1 also presents family covariances and correlations for the time averages of the log of hours worked per week and the log of weeks worked per year. For brothers, the correlations based upon the time averages for hours per week and weeks per year are only .14 and .18 respectively. But in view of the time average correlations for annual hours it is likely that these correlations are substantially reduced by the effects of measurement error and transitory variation in the time averages of hours worked per week and weeks worked per year.

The corresponding estimates for father-son pairs are .10 and .08, which are in line with the father-son correlation in the time average of annual hours of .06. (We have not produced separate estimates of weekly hours and yearly weeks worked using the method of moments approach.) Finally, we do not detect interesting sex differences in the relative strength of the family correlations between hours worked per week and weeks worked per year.

in labor market constraints that lead to unemployment, and the results for unemployment in Table 1 indicate that the unemployment rates of family members are correlated. The correlations based on time averages of the log of weeks of unemployment (with zeroes excluded from the calculation) are .07 for fathers and sons, .08 for brothers, .09 for sisters, and .10 for mothers and daughters. The correlations between fathers and daughters, mothers and sons, and brothers and sisters are weaker. In retrospect, our decision to work with the log of weeks of unemployment was a mistake. We therefore estimated the correlations in the level of weeks of unemployment and found the strongest correlations for brother pairs (.19), father-son pairs (.10), mother-daughter pairs (.08), and brother-sister pairs (.07).[24] For the level of weeks worked, the strongest correlations are found for sister pairs (.22), brother pairs (.15), mother-son and mother-daughter pairs (both are .10).

In contrast to the strong annual hours correlations for fathers and sons, brothers, sisters, and mothers and daughters, the correlations of the annual hours of brothers and sisters, fathers and daughters, and mothers and sons are close to zero. Why do hours tend to be correlated only among family members of the same sex? The result suggests that family factors influencing work hours are different for males and females. We speculate that preferences for leisure and correlations in labor market constraints are a key factor among men, most of whom choose to work more or less full time, while preferences and incentives for market work versus nonmarket work play a key role in the sisters' and mother-daughter correlations and in the total variance in the

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24. Altonji (1988) obtains correlations of .171 for brothers and .151 for fathers and sons using the PSID and hours of unemployment during the year. Part of the correlation might arise because of regional variation in labor market conditions that affects family members living in the same geographic area.

work hours of women. With data on hours spent on housework and child care, one could examine the correlation between leisure time of female and male family members. We conjecture that one would find larger mother-son and father-daughter correlations in hours if such a measure were used.[25]

Regression Results for Earnings, Hours, and Wages

As noted above, Tables 5a through 5d contain IV estimates of the regressions relating the earnings, hours, and wages of sons and daughters to the earnings, hours, and wages of fathers and mothers. The IV estimate of the effect of father's earnings on son's earnings is .210. However, the coefficient falls to -.005 (not significant) after we control for race, educations of the father and son, and location variables. The corresponding results for daughters are .335 and .179. For wages we obtain a coefficient of .282 with control set I and .098 with control set II for fathers and sons, and .238 and .118 for fathers and daughters. Overall the regression relationship between the wages and earnings of fathers and sons and fathers and daughters are similar to the relationships for family income. As before, we find that a substantial part of the relationship operates through education and race, particularly for sons.

The results for annual hours show a relatively weak relationship between annual hours of the father and the son. The OLS results are in line with the correlations between the time averages discussed earlier, and in view of the large variability in the time averages of father's annual hours, the small

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25. The Young Women and Mature Women NLS data sets do provide some information on time spent on child care and household chores which would make such an investigation possible. The Panel Study of Income Dynamics also contains the necessary data.

regression coefficient does not come as surprise. However, the IV estimates are much weaker than we would have expected given the method of moments results. The IV estimate with control set I is only .055, which is actually slightly smaller than the OLS estimate. In contrast, the regression coefficient implied by dividing the method of moments estimate of the covariance of hours of fathers and sons by the method of moments estimate of the variance of the hours of older men is .21. Since the time average of father's hours has a coefficient of .243 in the first stage IV equation for father's hours in 1965, we would have expected the second stage estimates to be roughly 4.12 (= 1/.243) times larger than the OLS estimate (of .063), which would be roughly consistent with the method of moments "regression coefficient" of .21. We are puzzled by the discrepancy. We have shown that it does not result from the fact that a smaller sample is available to compute the IV estimates.[26] The relationship for log hours per week is statistically significant under OLS for control set I but not for control set II, and the IV estimates are not statistically significant for either set of explanatory variables. The regression results for fathers and daughters do not show a relationship in annual or weekly hours worked, which is fully consistent with the correlations discussed earlier.

Mother's earnings has only a weak relationship to son's earnings, despite the fact that the mother's wage has a relatively strong link to the son's

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26. The IV sample is smaller because either log annual hours in 1965 or the average of the log of father's hours in years other than 1965 are missing in a few cases. (A similar explanation underlies the discrepancy in the OLS and IV sample sizes for the other variables in Tables 5a-5d.) We do obtain strong and statistically significant IV estimates of the link between log weeks worked by the father and log weeks worked by the son. As we point out below, the IV and method of moments estimates of the regression coefficient are quite close in the case of mothers and daughters.

wage (.341 with control set I). This reflects the facts that (1) hours of work of mothers and sons are only weakly related, and (2) the variance across women in work hours has a large effect on the variance in female earnings. The results for daughters and mothers are an interesting contrast: the coefficients on earnings and the wage rate are .348 and .325, respectively.

The strong link between the earnings of mothers and daughters reflects the fact that both work hours as well as the wage rates of mothers and daughters are strongly related. The IV coefficient on log weeks worked is .548 with a t-value of 4.5 using control set I. The corresponding coefficient for annual work hours is .347 with a t-statistic of 1.94. The latter result is basically consistent with the regression coefficient of (.275) implied by the method of moments estimates of the covariances and variances for mothers and daughters reported in Tables 3 and 4.

In summary, we find strong family links in earnings and in wages. We also find fairly strong correlations and regression relationships in the work hours of family members of the same sex (discounting the IV estimates for fathers and sons). Much of the effect of parental background on earnings and wage rates, particularly in the case of fathers and sons, operates through education and race.

III.3 Correlations Between Labor Market Outcomes of Individuals Related by Marriage

Tables 6 and 7 report covariances and correlations based on time averages of earnings, hours worked per week, weeks worked per year, and weeks unemployed per year for husbands and wives, fathers and sons-in-law, mothers and sons-in-law, brothers-in-law, fathers and daughters-in-law, mothers and

daughters-in-law, and sisters-in-law.[27] We focus our discussion on the relationships in earnings. We suspect that the correlations are downward biased because in most cases very few observations are available to compute the time averages for spouses. Consequently, we place greater emphasis on the covariances.

As an aid to interpreting the results, consider the following simple model of the relationship between individual earnings and spouse's earnings. Suppose that one's value in the labor market is related both to one's own earnings potential and to the earnings potential of one's blood relatives. To be specific, let the permanent earnings E_{ij} of child j from family i be determined by

$$(7) \quad E_{ij} = c_o + u_i + u_{ij}$$

where E_{ij} are the permanent earnings of a young woman j from family i, c_o is a constant, u_i are parental and sibling influences that have a common effect on the earnings of siblings, and u_{ij} is a child specific earnings factor that is uncorrelated across families and across children from family i.

Assume also that one's value in the marriage market depends on one's own earnings capacity and on the earnings capacity of one's siblings and parents. This assumption plus competition in the marriage market suggest that spouse's earnings capacity (and other traits that are valued in the marriage market) tend to be positively related to one's own earnings capacity and those of

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27. To be precise, Table 6 reports covariances and correlations of a young woman's reports of her husband's variables with the variables of the father, mother, and brother to whom the young woman can be matched. Similarly, young men supply the reports of their wives' variables for the covariances and correlations shown in Table 7.

one's relatives. Let the regression equation relating the earnings of the spouse of woman ij to the family i earnings component, u_i, and to her earnings, E_{ij}, be

$$(8) \quad E^S_{ij} = b_0 + b_1 u_i + b_2 E_{ij} + e^S_{ij}$$

where the error term e^S_{ij} is uncorrelated with u_i and E_{ij}.

Using (7) and (8) the covariances of the earnings of spouses, siblings and "in-laws" can be derived easily. For instance, the covariance between the earnings of spouses, E^S_{ij} and E_{ij}, is $(b_1 + b_2)*Var(u_i) + b_2*Var(u_{ij})$. The covariance between the earnings siblings ij and ij' implied by (7) is equal to $Var(u_i)$, where to keep the discussion simple we have ignored the important fact that the factor loading on the family component u_i may be different for young men than for young women. And the covariance between brothers-in-laws' earnings, E^S_{ij} and $E_{ij'}$, is $(b_1 + b_2)*Var(u_i)$.

If $b_1 = 0$ then the family effect, u_i, has no direct influence on spouse's earnings, and the covariance between the "in-laws'" earnings arises simply because u_i affects E^S_{ij} through E_{ij}. On the other hand, if only the income of the family matters, $(b_2 = 0)$, then the brother-in-law and spouse covariances are both equal to $b_1*Var(u_i)$, and both are less than the sibling covariance, $Var(u_i)$, when $b_1 < 1$. An increase in b_1 holding b_2 fixed raises the value of the in-law covariance relative to the sibling covariance, and relative to the spouse covariance. Consequently, the larger the value of the brother-in-law covariance relative to the sibling covariance and relative to the spouse covariance, the more likely it is that the family has influence on the permanent earnings of the spouse.

The earnings covariance is .168 for father and son-in-law pairs and .117 for fathers and son.[28] The earnings covariances (correlations) for brothers-in-law is .072 (.18), which compares to .117 (.28) for brothers. The earnings covariance for sisters-in-law is .105, which compares to .179 for sisters. The corresponding correlations are .13 and .23.[29]

Thus, we find that siblings-in-law covariances and correlations in earnings are somewhat weaker than the corresponding figures for sibling pairs. However, they seem large enough, particularly in light of the strong father and son-in-law covariance, to suggest that a family earnings component has an effect on the earnings capacity of spouses. The brothers-in-law and sisters-in-law covariances are also large relative to the covariances of spouses

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28. The correlation between the earnings of fathers and sons-in-law is estimated to be .32, which is actually larger than the corresponding estimate (.22) for fathers and sons in Table 1.

29. It is not difficult to fit the estimated earnings covariances to our simple model of family earnings relationships. First note that when $Var(u_i) = 1/3*Var(u_{ij})$, the implied siblings earnings correlation is .25 which is typical of the estimated siblings earnings covariances reported in Tables 3 and 1. (The sibling earnings correlation is $Corr(E_{ij}, E_{ij'}) = Var(u_i)/[Var(u_i) + Var(u_{ij})]$ which equals .25 when $Var(u_i) = 1/3*Var(u_{ij})$.)

Simply dividing the brothers-in-law covariance (.072) by the brothers earnings covariance (.117) suggests $(b_1 + b_2) = .62$. Similarly, the sisters-in-law and sisters results suggest $(b_1 + b_2) = .59$.

Also, when the spouses estimated earnings covariance-- equal to about .070 (see next footnote)-- is fitted into the model, the brothers and brothers-in-law results indicate that $b_2*Var(u_{ij}) = 0$, while the sisters' numbers imply $b_2*Var(u_{ij}) = -.033$. A richer earnings model which allows sex differences in the influences of spouses might be able to explain the differences in the moments implied by brothers' and the sisters' results; such a model is currently being developed.

earnings[30], which, in the context of the simple model sketched above, also points to an important direct effect of the family earnings component on the expected earnings capacity of the spouse. As a cautionary note, we do not wish to make too much of this interpretation, because the framework presented above ignores differences between men and women in family linkages, substitution in labor supply between husbands and wives, selectivity in who gets married, and other factors. In future work we plan to explore the issues systematically by combining a more elaborate version of the factor model sketched above with the factor model of earnings, hours and wages estimated in Chapter 2.

IV. Family Correlations in Turnover Behavior

Table 1 also provide estimates of the correlations across family members of the number of employers the individuals have worked for over the years of the survey. In the literature on wages and job mobility there has been considerable discussion of the importance of observed and unobserved personal characteristics in explaining the large differences found across individuals in the propensity to change jobs. A positive correlation in the separation rates of family members would arise if the desire and ability to "hold a job" has an important effect on turnover behavior and is correlated among family members. That is, mobility costs and personality traits that influence quits and layoffs may be correlated among family members. A number of authors have argued that personal characteristics related to turnover are negatively

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30. From Table 6 the covariance and correlation of spouses' earnings are .065 and .13 when the young woman supplies both reports. In Table 7, when the young man supplies reports on himself and his wife, the covariance is .072 and the correlation is .15.

related to productivity. As a result, ex post measures of turnover behavior, such as job seniority, are endogenous in a wage equation. We can investigate whether individual heterogeneity in turnover behavior is negatively related to productivity by examining the sign of the correlation between the turnover behavior of one family member with the wage rate of another. Job instability has been featured prominently in discussions of low income workers.[31] It is natural to ask if job instability is in part a family characteristic and whether the common family component of turnover behavior is negatively related to the family component of wages.

Before turning to the evidence, it is also important to point out that other theories of job mobility imply that variation across firms in wage offers as well as differences across specific firm-worker matches in productivity will lead to ex post differences in turnover even if the propensity of all workers to quit or induce a layoff or discharge is the same.[32] Some of the differences (such as initial wage offers) are readily observable, and workers may switch jobs in response to a higher wage offer. Other differences can be observed only after a trial period on the job, and will also lead to ex post differences in separation rates even if the expected value of separation rates are the same for all workers. What are the implications of wage offer and job match heterogeneity for family correlations among turnover and wages? If the expected value of separation rates are the same for all workers, then one would not expect job mobility to be correlated across family members. Also, simple matching models do not have a clear

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31. See, for example, Ballen and Freeman (1986) and Jackson and Montgomery (1986).

32. Garen (1988) provides a recent survey of the literature.

implication for the relationship between actual separation rates and productivity. Consequently, matching models in which differences in workers are unrelated to differences in expected mobility do not lead us to expect a correlation between the wages and mobility of one family member with the mobility patterns of another.

Unfortunately, the implications of matching and job search models of labor turnover for family correlations are less clear if the optimal amount of turnover associate with finding a good job match is related to occupation, ability, education, or other worker characteristics that are correlated among family members. In this case one might also find positive family correlations in turnover behavior even if matching and job search provide a complete explanation for turnover. The family correlations could also arise if the number and strength of personal contacts are correlated among family members and are an important determinant of turnover.

Table 1 reports the correlations in number of employers for sibling pairs and parent-child pairs. The correlation between the number of employers is positive and statistically significant in all case except for father-daughter pairs. For example, the correlation is .16 for brother pairs and .10 for father-son pairs. Altonji (1988) also finds a significant correlation between the separation rates of fathers and sons and between brothers. (This is the only other evidence on intra- and inter- generational links in turnover behavior of which we are aware.)[33]

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33. It is important to point out the variables in Tables 1 and 2 have not been adjusted for age differences. Since the variables measure the number of different employers and the number of different jobs over the years 1966 to 1981, the positive covariance in the ages and education of the brothers will lead to a positive covariance in the number of years since leaving school and in the number of years that they are in the labor market. This could lead to a covariance in the number of years that they are at risk to change employers

Tables 5a-5d presents OLS estimates of the relationship between the number of employers for matched family members. As noted above, a positive sibling correlation or intergenerational correlation in turnover rates is unlikely to arise from a simple matching model. Not much should be made of the specific values of the regression coefficients given that turnover behavior is highly dependent on years of labor market experience. However, we find a highly significant, positive relationship between the turnover rates of fathers and sons.[34] We also find a statistically significant relationship between the turnover rates of mothers and sons and mothers and daughters; however, we do not find a relationship between the turnover rates of fathers and daughters. Also note that the correlation and the covariance between the number of employers of brother-sister pairs are well below the values for sister pairs or brother pairs (.07 versus .13 and .16, respectively). We find stronger links between mothers and daughters than between mothers and sons, both in the correlations and in the regression coefficients (which appear in Tables 5c and 5d).

Thus, inter- and intragenerational links in turnover behavior appear to be stronger for persons of the same sex. We do not have a theory that can

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and might explain part of the positive correlation.

We re-estimated the brothers correlations of job turnovers and number of employers after first controlling for the ages and educations of the brothers; the resulting correlations were equal (at two decimal places) to the figures reported in Table 1.

(As noted earlier, the method of moments covariances, correlations, and variances reported in Tables 3 and 4 are based upon residuals from regressions of log earnings, the log hourly wage and log annual hours against time dummies and a cubic specification in age.)

34. The results do not change much when we add controls for education of the son and the father, race, residence in the South, and residence in an SMSA.

explain this finding. One explanation is that individual differences in labor supply behavior play a larger role in the turnover behavior of women. Recall from Section III.2 that correlations in hours worked were also much stronger for individuals of the same sex.

We do find that the wage rates of one family member are negatively correlated with the turnover behavior of other family members. The correlations are inconsistent in sign and are typically insignificant. (See the Appendix tables.) For example, the number of employers the father worked for from 1966 until retirement or age 60 has a correlation of -.043 with the son's log wage rate, but the p-value is .214 (see Table A2). On the other hand, the corresponding correlation for brother pairs is positive (though insignificant). Consequently, there is no strong evidence in the NLS data that the family component of turnover behavior is negatively related to wages rates. These results stand in contrast to those of Altonji (1988) for a sample of fathers and sons and brother pairs from the PSID. He finds a significant negative correlation between the separation rate of fathers and the wages of sons. He also finds that the separation rates of young men are negatively correlated with the wage rate of their brothers.

In summary, while there is consistent evidence from the NLS and PSID that turnover behavior depends on family characteristics, the evidence is conflicting on whether the family component of turnover behavior is negatively related to labor market productivity. In the NLS data, turnover behavior does not appear to play an important role in the inter- and intra-generational links in wages.

V. Are "Industry Wage Premiums" Correlated Across Generations?

In this section we ask whether the sons of men who work in industries that pay high wages (controlling for occupation and human capital) also tend to work in industries that pay high wages. We examine this correlation in part because we are interested in the magnitude of the link in the "industry component" of wages relative to the overall link. However, under certain assumptions, this correlation provides information about the extent to which industry wage differentials are market clearing differentials that compensate for differences across industries in worker quality or job characteristics, and the extent to which they are nonmarket clearing differentials that arise because firms choose to pay efficiency wages (or for other reasons.)

Assume first that employers select workers, and that family connections play an insignificant role in the allocation of workers across jobs. If industry differentials reflect differentials in worker quality, then one would expect the relation between the industry components of the father and the son's wage rates to be similar to the relationship between the wages of the father and the son. On the other hand, if industry wage premiums are rents that are unrelated to worker quality, and employers select workers without regard to family connections, then the industry wage effects of the father and the son should be unrelated. However, if family connections are important in the rationing of jobs, then fathers who are in industries that pay rents may be able get jobs for their children in the industry. In this case, both neoclassical and efficiency wage explanations for industry differentials would predict a positive relationship between the industry wage

effects of fathers and sons.[35]

To investigate the issue empirically, we first constructed estimates of industry wage components. We pooled the panel data on young men and older men and estimated a set of 18 coefficients on industry dummies using a regression equation that also included controls for education, experience, residence in the South, year dummies, residence in an SMSA, and a set of 11 dummy variables for occupation. Let λ_I denote the (18 × 1) vector of estimated industry coefficients and D_{ikt} denote the (18 × 1) vector of industry dummies for person k from family i in year t. We define D_{ik} (k=s, f) to be the average of D_{ikt} taken over the years in which the person meets the age and retirement criteria for inclusion in the analysis and has valid reports of his wage and industry. D_{ik} then is the average time each young man (k= s) or older man (k= f) spends in each of the 18 industries over his working history. We use the time average as a simple way of dealing with the fact that industry classifications vary from year to year due to measurement error and industry switches. We then form the time average of the industry wage premiums as $I_{ik} = \lambda'_I D_{ik}$.

We use matched data on father-son pairs to estimate the following regression relating the industry wage component of sons, I_{is}, to the industry wage component of their fathers, I_{if}:

$$I_{is} = \gamma_I I_{if} + B_1 X_{is} + B_2 X_{if} + \text{error}$$

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35. It is interesting to note that whether or not one believes in noncompetitive wage differentials has implications for how one views the role of networks in the labor market. If wage differentials are competitive, and one views personal connections as important, then one must view them as important because they convey information about job openings and the characteristics of workers and jobs. If differentials are noncompetitive, then connections may be important because they provide access to rents.

where X_{is} and X_{if} are control variables and the subscripts f and s denote the father and son. The regression results are presented in Table 8. The simple regression coefficient of the father's average industry premium is .227 with a t-value of 7.2.[36] Not surprisingly (given the way the industry coefficients are constructed) this estimate is relatively insensitive to adding controls for the father's and son's mean occupation coefficients (constructed in the same way as I_{if} and I_{is}) and to the addition of other control variables.[37] The estimate of .227 can be compared to the OLS and IV estimates of .273 and .282 relating the son's wage rate and the father's wage rate (see equation (6) above and Table 5a). However, the latter estimates fall to .086 and .098 when one includes controls for race, educations of the son and father, region and SMSA, and ages of the son and the father. When we add controls for the union status and occupation coefficients of both the father and the son, the father's industry coefficient falls by about one-third to .130 with a t-statistic of 3.0 (column 6 of Table 8).

Our estimate of .227 relating the industry wage components of fathers and sons is about half as large as the estimated relationship between the permanent wage rates of fathers and sons (.41) reported in Table 3. As we have noted earlier, these results are largely consistent with the hypothesis that unobserved ability differences underlie industry wage differentials (see Murphy and Topel (1987)) or the joint hypothesis that (a) industry differences are not market clearing and (b) family ties are important in gaining access to

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36. The simple correlation between I_{is} and I_{if} is .23.

37. The set of control variables includes: son's age and education, father's age and education (all in cubic specifications), son's race, residence in the South and in an SMSA.

jobs in high wage industries.[38] However, they are inconsistent with a nonmarket clearing model in which the family does not play a role in the allocation of jobs, where one would not expect industry wage premiums of sons and fathers to be related.

We have also examined intergenerational links in union status. For fathers and sons, we computed the time averages of dummy variables indicating membership in a collective bargaining unit. Table 9 reports the results of various regression specifications; the simple regression coefficient is .195 with a t-value of 5.1.[39] Since the mean of the collective bargaining variable for the young men in the matched sample is .32, this indicates that whether or

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38. If one assumes that the father is able to help his son get a job in his own industry but not in another industry, then in principle one can try to discriminate between the two hypotheses by examining the sample of sons who do not work in the same industries as their fathers. The fact that individuals frequently report more than one industry over a period of years complicates selection of the appropriate subsample of fathers and sons. However, one can take the inner product of the vector of time means of the industry dummies of the fathers and sons, and re-estimate over the sample for which the inner product is zero or below a certain threshold.

Unfortunately, a second problem is introduced: by eliminating fathers and sons who are in the same industry, one induces a systematic negative correlation between the industry coefficients of fathers and sons. Thus far, we have not found a simple econometric procedure to eliminate this bias. If one ignores the bias, and estimates the industry effects on the sample of fathers and sons who rarely work in the same industry, one obtains (unsurprisingly) a negative relationship between the average industry premiums. In future work, we plan to provide a descriptive analysis of the links between industries of fathers and sons and (hopefully) an estimation procedure that provides consistent estimates of the effects of the father's industry wage effect on the wage effect of the son when they are not in the same industry.

We did add the square of the father's industry premium to our regression specifications on the grounds that if family connections provide a young man the option to work in the father's industry, the option would only be exercised if the father worked in a high wage industry. This line of reasoning would lead one to expect a positive coefficient on the quadratic term; in fact, we obtained a positive and large (.183) but statistically insignificant coefficient on the father's squared industry component.

39. The simple correlation of father's and son's mean collective bargaining status is .22.

not one's father was a union member has a quantitatively large effect on the union membership probability. The coefficient falls to .108 when controls for father's age and education, son's age and education, residence in the South and in an SMSA, and race are added. The coefficient on father's collective bargaining status ranges between .099 and .113 and remains significant as controls for I_{is}, I_{if}, and the mean occupation coefficients of the father and the son are added.

Although the results are not reported, a series of regressions relating the son's mean occupation component of wages to his father's were also run. When one controls for education, age, residence, and race, the regression coefficient relating the son's occupation coefficient to the father's mean occupation coefficient (t-statistic) is .084 (2.9). (The simple regression coefficient is .298 with a t-value of 10.6, and the simple correlation is .34.) The positive relationship in the occupations ranked by wage rates is consistent with the literature on intergenerational links in the SES scores of occupation.[40]

VI. Conclusions

In this paper we examine the links between the labor market outcomes and family incomes of individuals who are related by blood or by marriage using panel data on siblings, their parents, and their spouses from the four original cohorts of the National Longitudinal Surveys of Labor Market Experience. The motivation for the analysis and implications for future research is spelled out in the introduction and in the text, and so here we will simply summarize the main empirical findings.

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[40]. See for example, Blau and Duncan (1967).

First, we find very strong intra and intergenerational correlations in family incomes. The sibling correlations are stronger for sisters than for brothers. Our preferred estimates are based upon the method of moments procedure. The correlations are .38 for brothers, .52 for sisters, and .56 for brothers and sisters, which are very large relative to most of the existing literature. The method of moments estimates of the intergenerational correlations of family income .34 for son-father pairs, .46 for daughter-father pairs, .55 for daughter-mother pairs, and .54 for son-mother pairs. The method of moments estimates for all intergenerational pairs except son-father are higher than any previous estimates for the U.S. that we are aware of. The regression analysis suggests that a one percent increase in the permanent family income of the parents raises the conditional mean of children's family income by .25 to .34 for sons and .32 to .42 for daughters. A substantial part of this effect operates through education and race.

Second, we find strong family links in earnings and in wages. Much of the effect of parental background on earnings and wage rates, particularly in the case of fathers and sons, operates through education and race.

Third, we also find fairly strong correlations and regression relationships in the work hours of family members of the same sex, discounting the IV estimates of the regression equation relating the work hours of fathers and sons. Our results suggest that family components plays an important role in hours determination.

Fifth, we find substantial covariances in the earnings of in-laws.

Sixth, we examine theories of labor turnover, and theories of wage structure. There is consistent evidence from the NLS and PSID (reported in Altonji (1988)) that turnover behavior depends on family characteristics, the

evidence is conflicting on whether the family component of turnover behavior is negatively related to labor market productivity. In the NLS data, turnover behavior does not appear to play an important role in the inter- and intra-generational links in wages. We also show that young men whose fathers work in high wage industries (controlling for human capital characteristics) tend themselves to work in high wage industries. We argue that the results are consistent with nonmarket clearing explanations for industry wage premiums (such as efficiency wages) only if family connections play a key role in gaining access to high wage firms.

Table 1
Summary of
Covariances & Correlations of Time Averages of
Selected Labor Market Variables
for Matched Family Members

Covariance
Correlation

Family Relationship

Labor Market Variable	Brother-Brother	Sister-Sister	Brother-Sister	Son-Father	Daughter-Father	Son-Mother	Daughter-Mother	Father-Mother	Husband-Wife
Log Family Income	.092	.201	.092	.100	.155	.134	.145	.313	.327
	.27	.37	.20	.27	.31	.31	.30	.82	.84
	295	286	854	690	623	975	1115	315	460
Log Earnings	.117	.179	.054	.117	.176	.084	.141	.193	.171
	.28	.23	.08	.22	.21	.13	.17	.31	.26
	420	360	1170	720	597	945	1082	220	327
Log Hourly Wage	.058	.053	.044	.076	.074	.046	.041	.089	.076
	.35	.36	.25	.36	.32	.27	.26	.44	.38
	408	371	1161	695	579	911	1082	214	315
Log Hours Worked per Week	.005	.015	-.005	.005	.001	-.005	.006	-.000	-.003
	.14	.09	-.06	.10	.01	-.05	.03	-.00	-.02
	427	396	1228	848	749	1022	1186	264	388
Log Weeks Worked per Year	.034	.046	-.000	.008	.005	.007	.042	.014	.021
	.18	.15	-.00	.08	.04	.03	.11	.10	.13
	393	344	1102	810	696	974	1156	279	407
Log Weeks Unemployed per Year	.001	.004	-.000	.001	.001	.001	.005	.002	.078
	.08	.09	-.01	.07	.05	.03	.10	.10	.08
	381	343	1093	809	687	971	1148	278	66
Log Annual Hours	.012	.074	-.004	.010	-.006	.008	.049	.021	.017
	.10	.13	-.01	.06	-.02	.02	.08	.06	.05
	369	253	931	793	615	921	928	259	379
Number of Employers	.512	.334	.206	.183	-.012	.243	.312	.078	.142
	.16	.13	.07	.10	-.01	.10	.14	.05	.10
	583	545	1692	1005	861	1256	1363	251	368
Number of Job Turnovers	.624	.365	.230	.121	-.001	.371	.330	.038	.133
	.17	.13	.07	.06	-.00	.12	.13	.02	.08
	583	545	1692	1005	861	1256	1363	251	368
Potential Number of Matches	621	646	1921	1099	988	1671	1848	345	492

Table 2

Summary of

Means and Variances of Time Averages of Selected Labor Market Variables for All Young Men, Young Women, Older Men, and Mature Women

Mean

Variance

Sample Size

Labor Market Variable	All Young Men	All Young Women	All Older Men	All Mature Women
Log Family Income	8.94	8.73	8.87	8.83
	.339	.477	.509	.461
	3569	3516	4471	4845
Log Earnings	8.56	7.63	8.62	7.60
	.454	.883	.610	.839
	4159	3900	3800	3974
Log Hourly Wage	1.10	0.64	1.04	0.57
	.176	.156	.270	.182
	4138	3907	3932	3996
Log Hours Worked per Week	3.76	3.46	3.74	3.42
	.038	.177	.069	.197
	4222	4034	4753	4264
Log Weeks Worked per Year	3.72	3.51	3.82	3.52
	.173	.380	.095	.334
	4044	3786	4779	4284
Log Weeks Unemployed per Year	1.33	1.23	1.33	1.23
	.010	.055	.012	.046
	4043	3737	4776	4271
Log Annual Hours Worked	7.58	7.07	7.57	6.99
	.148	.713	.214	.657
	3975	3314	4741	4155
Number of Employers	3.28	2.73	1.25	2.02
	3.42	2.56	.975	1.87
	5061	4608	4545	4117
Number of Job Turnovers	2.64	1.89	0.55	1.29
	4.06	2.77	1.08	2.33
	5061	4608	4545	4117
Potential Sample Size	5225	5159	5020	5083

Table 3
Summary of
Covariances & Correlations of Permanent Components of
Log Real Earnings, Log Real Wage Rates, and Log Annual Hours
Using Method of Moments Estimators
for Matched Family Members

Covariance
Correlation

Labor Market Variable	Brother-Brother	Sister-Sister	Brother-Sister	Son-Father	Daughter-Father	Son-Mother	Daughter-Mother	Father-Mother
Log Earnings	.085	.097	.088	.106	.133	.086	.103	.114
	.35	.26	.29	.39	.40	.29	.27	
Log Hourly Wage	.056	.042	.050	.067	.054	.045	.040	.053
	.42	.39	.41	.41	.38	.36	.35	.35
Log Annual Hours	.009	.054	.001	.007	.000	.004	.041	.018
	.34	.28	.01	.23	.00	.07	.24	.26
Log Family Income	.070	.118	.115	.080	.119	.136	.154	.258
	.38	.52	.56	.34	.46	.54	.55	.81

Table 4
Summary of
Variances of Permanent Components of
Log Real Earnings, Log Real Wages, and Log Annual Hours
for All Young Men, Young Women, Older Men, and Mature Women

Variance
Sample Size

Labor Market Variable	All Young Men	All Young Women	All Older Men	All Mature Women
Log Earnings	.243	.376	.299	.376
	36630	18067	6417	18284
Log Hourly Wage	.135	.107	.196	.120
	33468	17742	3487	27304
Log Annual Hours	.027	.197	.033	.149
	8922	3464	3485	11593
Log Family Income	.185	.226	.293	.345
	6785	4481	4336	15731

Table 5a

Regression Analysis of Relationship Between the Time Averages of the Son's Labor Market Outcomes and His Father's Labor Market Outcomes

Independent Variables:	Log Family Income	Log Earnings	Log Wage Rate	Log Hours per Week	Log Weeks Worked	Log Annual Hours Worked	Number of Employers
			SON'S LABOR MARKET OUTCOME				
			ORDINARY LEAST SQUARES				
Time Mean of Father's Corresponding Labor Market Outcome							
With Control Variable Set I[1]	.227	.191	.273	.074	.134	.063	.195
	(.032)	(.032)	(.028)	(.030)	(.067)	(.041)	(.058)
With Control Variable Set II[2]	.073	.022	.086	.053	.095	.030	.223
	(.042)	(.039)	(.035)	(.031)	(.069)	(.042)	(.058)
SAMPLE SIZE	690	720	695	847	809	792	1003
			INSTRUMENTAL VARIABLES[3]				
Father's Corresponding Labor Market Outcome							
With Control Variable Set I[1]	.249	.210	.282	.032	.611	.055	
	(.044)	(.037)	(.033)	(.065)	(.210)	(.131)	
With Control Variable Set II[2]	.073	-.005	.098	.007	.555	-.026	
	(.068)	(.052)	(.048)	(.068)	(.228)	(.149)	
SAMPLE SIZE	543	670	611	752	759	699	

standard errors are in parentheses
potential sample size= 1099

1. All equations contain the following set of control variables: child's age in 1966, age squared, age cubed, and parent's age in 1966, age squared, and age cubed.

2. All equations contain controls for child's race, child's education, education squared, education cubed, child's age in 1966, age squared, age cubed, child's mean residence in the South and in an SMSA, and parent's education, education squared, education cubed, parent's age in 1966, age squared, and age cubed.

3. In the IV equations, the following variables were used as measures of the father's (mother's) labor market outcomes: the log wage in 1966 (1967), log wage and salary income in 1965 (1966), log family income in 1965 (1967), log average hours worked per week in 1965 (1967), log weeks worked in 1965 (1967), and log annual hours in 1965 (1967). The instrumental variables consist of all the control variables in the corresponding labor market outcome equations (see notes 1 and 2 above) plus the father's (mother's) time average of the particular outcome variable constructed from all later years: for example, in the family income equation we use the average of log family income reports for the father (mother) for years after 1965 (1967).

Table 5b

Regression Analysis of Relationship Between the Time Averages of the Daughter's Labor Market Outcomes and Her Father's Labor Market Outcomes

Independent Variables:	Log Family Income	Log Earnings	Log Wage Rate	Log Hours per Week	Log Weeks Worked	Log Annual Hours Worked	Number of Employers
			DAUGHTER'S LABOR MARKET OUTCOME				
			ORDINARY LEAST SQUARES				
Time Mean of Father's Corresponding Labor Market Outcome							
With Control Variable Set I[1]	.296	.238	.238	.026	.124	-.004	-.012
	(.039)	(.045)	(.030)	(.057)	(.098)	(.079)	(.054)
With Control Variable Set II[2]	.158	.083	.096	.057	.139	.023	.009
	(.053)	(.054)	(.038)	(.058)	(.101)	(.082)	(.054)
SAMPLE SIZE	623	597	578	748	696	615	861
			INSTRUMENTAL VARIABLES[3]				
Father's Corresponding Labor Market Outcome							
With Control Variable Set I[1]	.322	.335	.238	.110	.042	-.072	
	(.049)	(.067)	(.036)	(.148)	(.266)	(.230)	
With Control Variable Set II[2]	.220	.179	.118	.184	.141	.058	
	(.080)	(.090)	(.048)	(.156)	(.281)	(.257)	
SAMPLE SIZE	485	540	475	656	641	530	

standard errors are in parentheses
potential sample size= 988

1. All equations contain the following set of control variables: child's age in 1966, age squared, age cubed, and parent's age in 1966, age squared, and age cubed.

2. All equations contain controls for child's race, child's education, education squared, education cubed, child's age in 1966, age squared, age cubed, child's mean residence in the South and in an SMSA, and parent's education, education squared, education cubed, parent's age in 1966, age squared, and age cubed.

3. In the IV equations, the following variables were used as measures of the father's (mother's) labor market outcomes: the log wage in 1966 (1967), log wage and salary income in 1965 (1966), log family income in 1965 (1967), log average hours worked per week in 1965 (1967), log weeks worked in 1965 (1967), and log annual hours in 1965 (1967). The instrumental variables consist of all the control variables in the corresponding labor market outcome equations (see notes 1 and 2 above) plus the father's (mother's) time average of the particular outcome variable constructed from all later years: for example, in the family income equation we use the average of log family income reports for the father (mother) for years after 1965 (1967).

Table 5c

Regression Analysis of Relationship Between the Time Averages of the Son's Labor Market Outcomes and His Mother's Labor Market Outcomes

Independent Variables:	Log Family Income	Log Earnings	Log Wage Rate	Log Hours per Week	Log Weeks Worked	Log Annual Hours Worked	Number of Employers
SON'S LABOR MARKET OUTCOME							
ORDINARY LEAST SQUARES							
Time Mean of Mother's Corresponding Labor Market Outcome							
With Control Variable Set I[1]	.285	.083	.264	-.025	.007	.010	.126
	(.029)	(.023)	(.034)	(.016)	(.023)	(.016)	(.037)
With Control Variable Set II[2]	.132	-.001	.059	-.030	-.006	.008	.129
	(.035)	(.024)	(.038)	(.016)	(.023)	(.016)	(.037)
SAMPLE SIZE	973	944	910	1021	986	920	1254
INSTRUMENTAL VARIABLES[3]							
Mother's Corresponding Labor Market Outcome							
With Control Variable Set I[1]	.340	.148	.341	-.002	.042	.016	
	(.042)	(.042)	(.050)	(.036)	(.079)	(.045)	
With Control Variable Set II[2]	.163	-.021	.124	-.019	-.019	-.038	
	(.073)	(.051)	(.072)	(.039)	(.087)	(.049)	
SAMPLE SIZE	808	565	553	640	675	554	

standard errors are in parentheses

potential sample size= 1671

1. All equations contain the following set of control variables: child's age in 1966, age squared, age cubed, and parent's age in 1966, age squared, and age cubed.

2. All equations contain controls for child's race, child's education, education squared, education cubed, child's age in 1966, age squared, age cubed, child's mean residence in the South and in an SMSA, and parent's education, education squared, education cubed, parent's age in 1966, age squared, and age cubed.

3. In the IV equations, the following variables were used as measures of the father's (mother's) labor market outcomes: the log wage in 1966 (1967), log wage and salary income in 1965 (1966), log family income in 1965 (1967), log average hours worked per week in 1965 (1967), log weeks worked in 1965 (1967), and log annual hours in 1965 (1967). The instrumental variables consist of all the control variables in the corresponding labor market outcome equations (see notes 1 and 2 above) plus the father's (mother's) time average of the particular outcome variable constructed from all later years: for example, in the family income equation we use the average of log family income reports for the father (mother) for years after 1965 (1967).

Table 5d

Regression Analysis of Relationship Between the Time Averages of the Daughter's Labor Market Outcomes and Her Mother's Labor Market Outcomes

Independent Variables:	Log Family Income	Log Earnings	Log Wage Rate	Log Hours per Week	Log Weeks Worked	Log Annual Hours Worked	Number of Employers
			DAUGHTER'S LABOR MARKET OUTCOME				
			ORDINARY LEAST SQUARES				
Time Mean of Mother's Corresponding Labor Market Outcome							
With Control Variable Set I[1]	.329	.170	.232	.037	.133	.081	.167
	(.032)	(.031)	(.027)	(.028)	(.030)	(.035)	(.033)
With Control Variable Set II[2]	.107	.072	.077	.039	.096	.071	.191
	(.040)	(.031)	(.030)	(.028)	(.031)	(.036)	(.033)
SAMPLE SIZE	1114	1082	1082	1186	1168	928	1363
			INSTRUMENTAL VARIABLES[3]				
Mother's Corresponding Labor Market Outcome							
With Control Variable Set I[1]	.422	.348	.325	.101	.548	.347	
	(.048)	(.067)	(.050)	(.103)	(.121)	(.179)	
With Control Variable Set II[2]	.152	.263	.181	.176	.485	.337	
	(.092)	(.091)	(.077)	(.121)	(.126)	(.187)	
SAMPLE SIZE	909	677	643	758	817	579	

standard errors are in parentheses
potential sample size= 1848

1. All equations contain the following set of control variables: child's age in 1966, age squared, age cubed, and parent's age in 1966, age squared, and age cubed.

2. All equations contain controls for child's race, child's education, education squared, education cubed, child's age in 1966, age squared, age cubed, child's mean residence the South and in an SMSA, and parent's education, education squared, parent's age in 1966, age squared, and age cubed.

3. In the IV equations, the following variables were used as measures of the father's (mother's) labor market outcomes: the log wage in 1966 (1967), log wage and salary income in 1965 (1966), log family income in 1965 (1967), log average hours worked per week in 1965 (1967), log weeks worked in 1965 (1967), and log annual hours in 1965 (1967). The instrumental variables consist of all the control variables in the corresponding labor market outcome equations (see notes 1 and 2 above) plus the father's (mother's) time average of the particular outcome variable constructed from all later years: for example, in the family income equation we use the average of log family income reports for the father (mother) for years after 1965 (1967).

Table 6
Summary of
Covariances & Correlations of Time Averages of
Selected Labor Market Variables
for Young Women's Reports of Their Husbands and Other
Matched Family Members

Covariance
Correlation
Sample Size

Family Relationship

Labor Market Variable	Young Woman-Husband	Husband-Father-in-Law	Husband-Mother-in-Law	Husband-Brother-in-Law
Log Earnings	.065	.168	.081	.072
	.13	.32	.16	.18
	3209	556	1035	1057
Log Hours Worked	-.001	.002	.002	.001
per Week	-.02	.03	.03	.02
	3221	635	1046	1036
Log Weeks Worked	.003	-.001	.010	.009
per Year	.02	-.02	.06	.07
	3031	629	1063	977
Log Weeks Unemployed	.001	-.000	-.014	-.007
per Year	.00	-.00	-.07	-.08
	904	164	310	317
Log Annual Hours	.000	.003	.007	.011
	.00	.02	.03	.07
	2630	623	1003	948

Table 7
Summary of
Covariances & Correlations of Time Averages of
Selected Labor Market Variables
for Young Men's Reports of Their Wives and Other
Matched Family Members

Covariance
Correlation
Sample Size

Family Relationship

Labor Market Variable	Young Man-Wife	Wife-Father-in-Law	Wife-Mother-in-Law	Wife-Sister-in-Law
Log Earnings	.076	.089	.078	.105
	.15	.13	.09	.13
	2939	509	714	814
Log Hours Worked	-.004	.001	.012	.016
per Week	-.05	.02	.06	.09
	2189	440	587	647
Log Weeks Worked	.018	.005	.016	.038
per Year	.07	.03	.04	.08
	2694	544	695	726
Log Annual Hours	-.007	.016	.055	.123
	-.03	.05	.07	.15
	2124	439	575	539

Table 8
Regression Analysis of Relationship Between Father's and Son's Industry Components

Independent Variables:	Dependent Variable: Son's Mean Industry Wage Component (1)	(2)	(3)	(4)	(5)	(6)
Father's Mean Industry Wage Component	.227 (7.2)	.227 (7.2)	.224 (7.1)	.223 (7.1)	.203 (6.3)	.130 (3.0)
Son's Mean Occupation Component			-.110 (-2.7)	-.118 (-2.9)	-.114 (-2.7)	-.151 (-3.0)
Father's Mean Occupation Component				.071 (2.0)	.089 (2.5)	.161 (3.5)
Son's Mean Collective Bargaining Status					.059 (5.6)	.063 (5.2)
Father's Mean Collective Bargaining Status						-.001 (-0.1)
Controls Included?	no	yes	yes	yes	yes	yes
R^2	.06	.14	.14	.15	.20	.26
N	894	888	887	887	791	542

Notes:

1. t- statistics are in parentheses.

2. Control variables are the following: son's education, father's education, son's age, father's age, (all in cubic specifications), indicators for race, and for residence in the South and residence in an SMSA.

3. The dependent variable has mean equal to .14 with a standard error of .120. The father's corresponding variable has mean equal to .14 and standard error of .127.

Table 9
Regression Analysis of Relationship Between Father's and Son's Collective Bargaining Status

Independent Variables:	Dependent Variable: Son's Mean Collective Bargaining (1)	(2)	(3)	(4)	(5)	(6)
Father's Mean Collective Bargaining Status	.195 (5.1)	.108 (2.8)	.099 (2.6)	.104 (2.6)	.113 (2.9)	.100 (2.5)
Son's Mean Industry Component			.853 (5.8)	.862 (5.8)		.771 (5.2)
Son's Mean Occupation Component					-.921 (-5.3)	-.755 (4.4)
Father's Mean Industry Component				-.055 (-0.4)		-.015 (-0.1)
Father's Mean Occupation Component					.043 (0.3)	-.099 (-0.6)
Controls Included?	no	yes	yes	yes	yes	yes
R^2	.05	.17	.22	.22	.21	.25
N	544	543	543	543	542	542

Notes:
1. t- statistics are in parentheses.

2. Control variables are the following: son's education, father's education, son's age, father's age, (all in cubic specifications), indicators for race, and for residence in the South and residence in an SMSA.

3. The dependent variable has mean equal to .32 with a standard error of .414. The father's corresponding variable has mean .37 with a standard error of .457.

Table A1
Correlations Among Time Averages of
Selected Labor Market Variables of
Young Men and Brothers

Correlation
p-value
Sample Size

Young Men's Variables

Brother's Variables	BMFINC	BMEARN	BMWAGE	BMLERWK	BMLWW	BMLWU	BNUMEMP	BTURNOV
BMFINC	0.26785	0.29525	0.32287	-0.00920	0.07019	0.06171	-0.07398	-0.04031
MEAN FAMILY INCOME (IN LOGS)	0.0001	0.0001	0.0001	0.8646	0.1980	0.2586	0.1544	0.4382
	285	342	343	346	338	337	372	372
BMEARN	0.24952	0.27868	0.31409	0.08295	0.19186	0.14593	-0.03060	0.00509
MEAN INCOME FROM WAG&SAL (IN LOGS)	0.0001	0.0001	0.0001	0.0888	0.0001	0.0031	0.5118	0.9131
	353	420	418	422	409	408	462	462
BMWAGE	0.28204	0.28557	0.35011	0.10211	0.09499	0.06064	-0.01878	0.01308
MEAN HOURLY WAGE RATE (IN LOGS)	0.0001	0.0001	0.0001	0.0383	0.0583	0.2280	0.6912	0.7820
	344	410	408	412	398	397	450	450
BMLERWK	0.07779	0.13738	0.12145	0.14172	0.04547	0.05667	0.05883	0.10368
MEAN LOG # HRS WORKD PR WEEK 67-81	0.1424	0.0047	0.0126	0.0033	0.3567	0.2511	0.2040	0.0249
	357	422	421	427	413	412	468	468
BMLWW	0.07893	0.14424	0.07902	0.06634	0.18343	0.06917	0.09265	0.10560
MEAN LOG # WKS WORKD PR YEAR 66-80	0.1531	0.0044	0.1197	0.1883	0.0003	0.1773	0.0543	0.0282
	329	389	389	395	383	382	432	432
BMLWU	0.05116	0.16864	0.11107	0.08838	0.24162	0.08161	0.08934	0.10257
MEAN LOG # WKS UNEMPLD PR YR 66-80	0.3549	0.0008	0.0285	0.0794	0.0001	0.1113	0.0636	0.0331
	329	389	389	395	383	382	432	432
BNUMEMP	0.01041	0.11061	0.05069	0.02958	-0.02584	0.02760	0.16303	0.14963
# DIFFT EMPLOYERS OVER YRS 66-81	0.8301	0.0123	0.2541	0.5038	0.5671	0.5414	0.0001	0.0003
	427	512	508	513	493	492	583	583
BTURNOV	0.05038	0.13793	0.06155	0.07264	0.00349	0.05927	0.15394	0.16840
# JOB TURNOVERS OVER YRS 66-81	0.2990	0.0018	0.1660	0.1003	0.9385	0.1884	0.0002	0.0001
	427	512	508	513	493	492	583	583

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
BMFINC	435	8.94898478	0.58457120	BMFINC	377	8.86968875	0.64499869
BMEARN	523	8.57192181	0.67443341	BMEARN	473	8.47427270	0.66324582
BMWAGE	519	1.10481303	0.40271647	BMWAGE	460	1.04541711	0.40560557
BMLERWK	524	3.78240371	0.17496858	BMLERWK	478	3.73618087	0.18427594
BMLWW	504	3.70755194	0.46217862	BMLWW	441	3.72132874	0.44894458
BMLWU	503	1.33651255	0.06670024	BMLWU	441	1.31982820	0.14789964
BNUMEMP	604	3.35264901	1.80834887	BNUMEMP	599	3.38564274	1.74547505
BTURNOV	604	2.86225166	1.94752866	BTURNOV	599	2.70784641	1.91799833

Table A2
Correlations Among Time Averages of
Selected Labor Market Variables of
Sons and Fathers

Correlation
p-value
Sample Size

Father's Variables	Son's Variables: MMFINC	MMEARN	MMWAGE	MMLHRWK	MMLWW	MMLWU	MNUMEMP	MTURNOV
MMFINC	0.27435	0.25984	0.34316	-0.00063	0.05673	0.04690	-0.00931	0.02217
MEAN TOT NET FAM INC <RETMNT (LOG)	0.0001	0.0001	0.0001	0.9856	0.1124	0.1896	0.7695	0.4853
	690	819	814	826	784	784	993	993
MMEARN	0.23680	0.22475	0.31802	-0.03014	0.03312	0.01885	-0.01945	-0.00987
MEAN INC FRM WAG&SAL <RETMNT (LOG)	0.0001	0.0001	0.0001	0.4193	0.3882	0.6234	0.5701	0.7731
	599	720	715	720	681	681	855	855
MMWAGE	0.23731	0.22248	0.36292	0.03606	0.02626	0.03563	-0.05424	-0.01901
MEAN HOURLY WAGE < RETIREMENT (LOG)	0.0001	0.0001	0.0001	0.3404	0.4990	0.3590	0.1143	0.5802
	585	701	695	701	665	665	849	849
MMLHRWK	0.06052	0.00809	0.04288	0.09842	0.00491	0.02258	0.02130	0.05039
MEAN LOG # HRS WORKD PR WEEK 65-83	0.1084	0.8149	0.2161	0.0041	0.8894	0.5226	0.4952	0.1064
	705	840	834	848	805	804	1028	1028
MMLWW	0.08819	0.06080	0.07032	0.02579	0.07874	0.07473	0.00004	0.02612
MEAN LOG # WKS WORKD PR YEAR 65-83	0.0188	0.0773	0.0416	0.4517	0.0250	0.0336	0.9990	0.4015
	709	845	840	854	810	809	1034	1034
MMLWU	0.07304	0.04909	0.06550	0.01881	0.06898	0.06886	0.00762	0.03048
MEAN LOG # WKS UNEMPLD PR YR 65-83	0.0519	0.1539	0.0577	0.5830	0.0497	0.0502	0.8068	0.3275
	709	845	840	854	810	809	1034	1034
MNUMEMP	-0.05604	-0.01419	-0.04343	-0.05990	-0.04528	0.00138	0.10434	0.05112
# DIFFT EMPLOYERS OVER YRS 66-83	0.1400	0.6838	0.2139	0.0837	0.2025	0.9690	0.0009	0.1053
	695	826	821	835	794	794	1005	1005
MTURNOV	-0.04088	0.01662	-0.00690	-0.01226	0.00182	0.04091	0.07780	0.06172
# JOB TURNOVERS OVER YRS 66-83	0.2818	0.6334	0.8435	0.7236	0.9591	0.2495	0.0136	0.0505
	695	826	821	835	794	794	1005	1005

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
MMFINC	720	8.99599105	0.55514690	MMFINC	1025	9.01926414	0.6649556
MMEARN	862	8.57389244	0.67495675	MMEARN	886	8.68951833	0.7522646
MMWAGE	857	1.11660109	0.42159527	MMWAGE	881	1.10229976	0.53071838
MMLHRWK	871	3.74704658	0.20205401	MMLHRWK	1065	3.76518621	0.2324143
MMLWW	825	3.70246899	0.44863394	MMLWW	1071	3.84279891	0.2383780
MMLWU	824	1.32878434	0.10059962	MMLWU	1071	1.34028703	0.08778533
MNUMEMP	1061	3.26390198	1.80097129	MNUMEMP	1042	1.24568138	0.9767250
MTURNOV	1061	2.61922714	1.95036711	MTURNOV	1042	0.56429942	1.0024906

Table A3
Correlations Among Time Averages of
Selected Labor Market Variables of
Sons and Mothers

Correlation
p-value
Sample Size

	Son's Variables							
Mother's Variables	SMFINC	SMEARN	SMWAGE	SMLERWK	SMLWW	SMLWU	SNUMEMP	STURNOV
WMFINC	**0.30870**	0.27206	0.34189	0.08697	0.12446	0.12690	0.01211	0.04207
MEAN FAMILY INCOME (IN LOGS)	0.0001	0.0001	0.0001	0.0026	0.0001	0.0001	0.6345	0.0985
	975	1183	1175	1195	1119	1119	1544	1544
WMEARN	0.18331	**0.12769**	0.17694	0.02326	0.03661	0.03762	0.00494	0.00517
MEAN INCOME FROM WG&SAL (IN LOGS)	0.0001	0.0001	0.0001	0.4734	0.2748	0.2617	0.8630	0.8569
	774	945	934	952	892	892	1220	1220
WMWAGE	0.24405	0.17708	**0.26680**	0.00759	0.01122	0.02216	-0.00613	0.01171
MEAN HOURLY WAGE RATE (IN LOGS)	0.0001	0.0001	0.0001	0.8173	0.7405	0.5132	0.8317	0.6846
	755	921	911	930	873	873	1206	1206
WMLERWK	0.04480	0.02635	0.05598	**-0.05138**	0.02579	0.01793	-0.00402	-0.02051
MEAN LOG # ERS WORKD PR WEEK 67-84	0.1954	0.4018	0.0764	0.1006	0.4249	0.5789	0.8837	0.4549
	837	1015	1003	1022	960	960	1329	1329
WMLWW	0.11821	0.09746	0.07135	0.04214	**0.02722**	0.03185	0.03203	0.02895
MEAN LOG # WKS WORKD PR YEAR 67-84	0.0006	0.0017	0.0227	0.1747	0.3962	0.3208	0.2407	0.2890
	848	1029	1019	1039	974	974	1343	1343
WMLWU	0.11713	0.11219	0.07512	0.05679	0.03606	**0.03390**	0.03852	0.03640
MEAN LOG # WKS UNEMPLD PR YR 67-84	0.0007	0.0003	0.0187	0.0678	0.2616	0.2913	0.1589	0.1831
	844	1025	1015	1035	971	971	1339	1339
WNUMEMP	-0.07869	-0.06534	-0.08111	-0.01242	-0.00061	-0.02214	**0.09729**	0.10786
# DIFFT EMPLOYERS OVER YRS 67-84	0.0306	0.0425	0.0122	0.6992	0.9853	0.5051	0.0006	0.0001
	795	964	954	970	909	909	1256	1256
WTURNOV	-0.06966	-0.04749	-0.09706	0.00571	0.01226	-0.01424	0.09853	**0.12066**
# JOB TURNOVERS OVER YRS 67-84	0.0496	0.1407	0.0027	0.8590	0.7121	0.6680	0.0005	0.0001
	795	964	954	970	909	909	1256	1256

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
SMFINC	1004	8.88224651	0.63449188	WMFINC	1599	8.78185702	0.68421014
SMEARN	1219	8.46063716	0.71173909	WMEARN	1258	7.44408290	0.94516679
SMWAGE	1211	1.04178913	0.42073483	WMWAGE	1244	0.48339998	0.40172855
SMLERWK	1234	3.73860891	0.22673824	WMLERWK	1373	3.40906255	0.45839787
SMLWW	1154	3.72356021	0.44131858	WMLWW	1392	3.48733496	0.62268848
SMLWU	1154	1.32480685	0.11687655	WMLWU	1388	1.21900723	0.24004305
SNUMEMP	1608	3.42164179	1.80439325	WNUMEMP	1296	1.92669753	1.37827497
STURNOV	1608	2.73072139	1.95124174	WTURNOV	1296	1.22530864	1.56757932

Table A4
Correlations Among Time Averages of
Selected Labor Market Variables of
Brothers and Sisters

Correlation
p-value
Sample Size

Sister's Variables	BMFINC	BMEARN	BMWAGE	BMLHRWK	BMLWW	BMLWU	BNUMEMP	BTURNOV
GMFINC	0.19781	0.19289	0.26592	0.02432	0.00716	0.03579	-0.07837	-0.06461
MEAN FAMILY INCOME (IN LOGS)	0.0001	0.0001	0.0001	0.4323	0.8228	0.2627	0.0059	0.0233
	854	1034	1029	1045	982	981	1233	1233
GMEARN	0.14614	0.08063	0.14718	-0.01438	0.00242	-0.01859	-0.09755	-0.09164
MEAN INCOME FROM WAG&SAL (IN LOGS)	0.0001	0.0058	0.0001	0.6215	0.9356	0.5351	0.0002	0.0006
	968	1170	1165	1181	1117	1116	1411	1411
GMWAGE	0.20222	0.15560	0.25118	-0.00252	0.00676	0.00337	-0.05991	-0.04010
MEAN HOURLY WAGE RATE (IN LOGS)	0.0001	0.0001	0.0001	0.9313	0.8219	0.9108	0.0247	0.1328
	960	1167	1161	1177	1111	1110	1406	1406
GMLHRWK	-0.04064	-0.09098	-0.06265	-0.05911	-0.01812	-0.03000	-0.04593	-0.06129
MEAN LOG # HRS WORKD PR WEEK 68-82	0.1996	0.0015	0.0295	0.0384	0.5376	0.3075	0.0789	0.0190
	998	1214	1208	1228	1160	1159	1465	1465
GMLWW	0.07520	0.04993	0.03861	0.05291	-0.00015	0.00158	-0.06954	-0.08217
MEAN LOG # WKS WORKD PR YEAR 68-82	0.0203	0.0900	0.1913	0.0709	0.9961	0.9581	0.0098	0.0023
	953	1154	1147	1166	1102	1101	1379	1379
GMLWU	0.05103	0.02698	0.03226	0.01660	-0.01098	-0.01207	-0.06577	-0.07147
MEAN LOG # WKS UNEMPLD PR YR 68-82	0.1166	0.3614	0.2766	0.5725	0.7168	0.6903	0.0149	0.0081
	947	1147	1139	1158	1094	1093	1371	1371
GNUMEMP	0.06832	0.03092	0.05079	0.03313	0.00068	-0.00817	0.06936	0.07788
# DIFFT EMPLOYERS OVER YRS 68-82	0.0220	0.2527	0.0610	0.2175	0.9803	0.7684	0.0043	0.0013
	1124	1371	1361	1387	1302	1301	1692	1692
GTURNOV	0.08422	0.05149	0.07238	0.04184	0.01099	0.00314	0.05626	0.07027
# JOB TURNOVERS OVER YRS 68-82	0.0047	0.0566	0.0076	0.1193	0.6919	0.9098	0.0207	0.0038
	1124	1371	1361	1387	1302	1301	1692	1692

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
BMFINC	1215	8.83289187	0.64938507	GMFINC	1252	8.63047396	0.74604273
BMEARN	1497	8.44208753	0.71940052	GMEARN	1437	7.62984918	0.93478365
BMWAGE	1486	1.02901971	0.43941944	GMWAGE	1435	0.61805095	0.39022845
BMLHRWK	1516	3.73979589	0.20765965	GMLHRWK	1493	3.49014277	0.39140111
BMLWW	1422	3.69584603	0.43254518	GMLWW	1402	3.50751262	0.62570340
BMLWU	1421	1.32219729	0.10829522	GMLWU	1394	1.22812330	0.24330012
BNUMEMP	1872	3.39155983	1.85497535	GNUMEMP	1732	2.74769053	1.61677021
BTURNOV	1872	2.71420940	1.98202802	GTURNOV	1732	1.86836028	1.66278911

Table A5
Correlations Among Time Averages of
Selected Labor Market Variables of
Young Women and Sisters

Correlation
p-value
Sample Size

	Young Woman's Variables							
Sister's Variables	GMFINC	GMEARN	GMWAGE	GMLHRWK	GMLWW	GMLWU	GNUMEMP	GTURNOV
SMFINC	**0.37347**	0.19400	0.26737	0.00916	0.04243	0.05177	0.07507	0.12509
MEAN FAMILY INCOME (IN LOGS)	0.0001	0.0006	0.0001	0.8690	0.4626	0.3700	0.1501	0.0162
	286	306	316	327	302	302	369	369
SMEARN	0.20920	**0.23128**	0.28406	0.06598	0.14976	0.10998	0.07708	0.10312
MEAN INCOME FROM WAG&SAL (IN LOGS)	0.0002	0.0001	0.0001	0.1999	0.0050	0.0397	0.1109	0.0327
	323	360	366	379	350	350	429	429
SMWAGE	0.29902	0.23707	**0.35651**	0.00019	0.09178	0.06652	0.06229	0.09325
MEAN HOURLY WAGE RATE (IN LOGS)	0.0001	0.0001	0.0001	0.9970	0.0851	0.2125	0.1958	0.0525
	326	364	371	382	353	353	433	433
SMLHRWK	-0.01823	0.00023	-0.01982	**0.08964**	0.04990	0.04552	0.04614	0.04495
MEAN LOG # HRS WORKD PR WEEK 68-82	0.7399	0.9965	0.6993	0.0748	0.3405	0.3853	0.3304	0.3430
	334	376	382	396	367	366	447	447
SMLWW	0.10346	0.06385	0.13499	0.07433	**0.14525**	0.10902	0.01411	0.01168
MEAN LOG # WKS WORKD PR YEAR 68-82	0.0663	0.2315	0.0105	0.1530	0.0070	0.0433	0.7731	0.8113
	316	353	359	371	344	344	420	420
SMLWU	0.07863	0.02184	0.11694	0.04483	0.12444	**0.09440**	0.00082	-0.00331
MEAN LOG # WKS UNEMPLD PR YR 69-82	0.1639	0.6831	0.0269	0.3898	0.0212	0.0808	0.9867	0.9461
	315	352	358	370	343	343	419	419
SNUMEMP	0.03700	0.01863	0.04046	-0.00651	-0.04514	-0.03462	**0.13375**	0.12412
# DIFFT EMPLOYERS OVER YRS 68-82	0.4662	0.6958	0.3903	0.8881	0.3527	0.4766	0.0018	0.0037
	390	443	453	469	426	425	545	545
STURNOV	0.04163	0.01954	0.02507	-0.04146	-0.03170	-0.01891	0.13608	**0.13253**
# JOB TURNOVERS OVER YRS 68-82	0.4123	0.6818	0.5946	0.3703	0.5140	0.6976	0.0015	0.0019
	390	443	453	469	426	425	545	545

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
GMFINC	423	8.75641279	0.69575256	SMFINC	397	8.58809702	0.77762646
GMEARN	477	7.74034655	0.89353725	SMEARN	459	7.74537284	0.89158849
GMWAGE	490	0.66568278	0.39148023	SMWAGE	462	0.64869693	0.37319593
GMLHRWK	507	3.48829290	0.42869323	SMLHRWK	474	3.51407106	0.38214244
GMLWW	458	3.53754845	0.59748806	SMLWW	445	3.57402129	0.57014700
GMLWU	457	1.23831950	0.22708133	SMLWU	444	1.25062942	0.21491557
GNUMEMP	594	2.79124579	1.58519418	SNUMEMP	586	2.77474403	1.53826754
GTURNOV	594	1.95286195	1.66639240	STURNOV	586	1.88225256	1.60601190

Table A6
Correlations Among Time Averages of
Selected Labor Market Variables of
Daughters and Fathers

Correlation
p-value
Sample Size

	Daughter's Variables						
Father's Variables	GMFINC	GMEARN	GMWAGE	GMLHRWK	GMLWW	GMLWU	GNUMEMP	GTURNOV
MMFINC	0.31299	0.16572	0.31826	-0.08060	0.03234	0.03373	0.08783	0.10569
MEAN TOT NET FAM INC <RETMNT (LOG)	0.0001	0.0001	0.0001	0.0289	0.3997	0.3830	0.0098	0.0019
	623	709	707	735	680	671	864	864
MMEARN	0.25419	0.21434	0.31605	-0.01327	0.07677	0.08728	0.09311	0.10776
MEAN INC FRM WAG&SAL <RETMNT (LOG)	0.0001	0.0001	0.0001	0.7421	0.0672	0.0388	0.0118	0.0035
	525	597	595	617	569	561	731	731
MMWAGE	0.32576	0.20746	0.32259	-0.02216	0.04276	0.03906	0.06532	0.08046
MEAN WAGE < RETIREMENT (LOG)	0.0001	0.0001	0.0001	0.5896	0.3182	0.3654	0.0809	0.0315
	512	579	579	595	547	539	715	715
MMLHRWK	0.05053	0.12049	0.07755	0.00661	0.00476	0.01041	0.06430	0.07795
MEAN LOG # HRS WORKD PR WEEK 65-83	0.2043	0.0012	0.0376	0.8568	0.9004	0.7856	0.0566	0.0207
	633	722	719	749	694	685	880	880
MMLWW	0.11024	0.09175	0.04191	-0.02715	0.03610	0.03515	0.01406	0.02105
MEAN LOG # WKS WORKD PR YEAR 65-83	0.0054	0.0135	0.2607	0.4570	0.3416	0.3577	0.6762	0.5320
	636	724	722	753	696	687	884	884
MMLWU	0.09283	0.09257	0.04781	-0.00729	0.04419	0.04604	0.02519	0.03063
MEAN LOG # WKS UNEMPLD PR YR 65-83	0.0192	0.0127	0.1998	0.8419	0.2443	0.2281	0.4544	0.3630
	636	724	721	752	696	687	884	884
MNUMEMP	-0.02412	-0.00647	-0.00761	0.03418	-0.05759	-0.05224	-0.00754	-0.02176
# DIFFT EMPLOYERS OVER YRS 66-83	0.5482	0.8638	0.8402	0.3554	0.1338	0.1768	0.8251	0.5236
	622	706	704	733	679	670	861	861
MTURNOV	-0.03627	-0.01381	-0.02857	0.05437	-0.07532	-0.06456	0.00582	-0.00047
# JOB TURNOVERS OVER YRS 66-83	0.3665	0.7141	0.4492	0.1414	0.0498	0.0950	0.8647	0.9890
	622	706	704	733	679	670	861	861

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
GMFINC	652	8.77262992	0.69939512	MMFINC	936	9.01979965	0.69072630
GMEARN	741	7.74771004	0.94095788	MMEARN	798	8.67935380	0.85776234
GMWAGE	739	0.69587494	0.42082681	MMWAGE	786	1.09932343	0.56074908
GMLHRWK	769	3.47027528	0.42176496	MMLHRWK	958	3.75238655	0.29888391
GMLWW	711	3.53858016	0.61430912	MMLWW	963	3.82750698	0.28429811
GMLWU	702	1.24109363	0.22768111	MMLWU	962	1.33716690	0.09162740
GNUMEMP	906	2.78918322	1.57070347	MNUMEMP	937	1.24119530	1.00929961
GTURNOV	906	1.92715232	1.67503345	MTURNOV	937	0.59765208	1.08865301

Table A7
Correlations Among Time Averages of
Selected Labor Market Variables of
Daughters and Mothers

Correlation
p-value
Sample Size

	Daughter's Variables							
Mother's Variables	GMFINC	GMEARN	GMWAGE	GMLHRWK	GMLWW	GMLWU	GNUMEMP	GTURNOV
MMFINC	0.29619	0.19534	0.30843	-0.07192	0.10577	0.11844	0.08377	0.09997
MEAN FAMILY INCOME (IN LOGS)	0.0001	0.0001	0.0001	0.0076	0.0001	0.0001	0.0008	0.0001
	1115	1320	1336	1376	1306	1303	1612	1612
MMEARN	0.18107	0.16722	0.16436	0.04382	0.10945	0.10931	0.04967	0.04720
MEAN INCOME FROM WG&SAL (IN LOGS)	0.0001	0.0001	0.0001	0.1435	0.0003	0.0004	0.0714	0.0867
	898	1082	1099	1116	1064	1061	1318	1318
MMWAGE	0.19038	0.20077	0.25651	0.01903	0.05912	0.06444	0.07004	0.08601
MEAN HOURLY WAGE RATE (IN LOGS)	0.0001	0.0001	0.0001	0.5280	0.0551	0.0368	0.0114	0.0019
	879	1067	1082	1102	1053	1050	1306	1306
MMLHRWK	0.13956	0.05252	0.07882	0.03499	0.02882	0.02304	-0.02755	-0.03456
MEAN LOG # HRS WORKD PR WEEK 67-84	0.0001	0.0754	0.0072	0.2285	0.3322	0.4390	0.3021	0.1954
	954	1147	1162	1186	1134	1131	1405	1405
MMLWW	0.13607	0.14187	0.11504	0.07704	0.11224	0.10232	0.08002	0.08614
MEAN LOG # WKS WORKD PR YEAR 67-84	0.0001	0.0001	0.0001	0.0073	0.0001	0.0005	0.0024	0.0011
	972	1165	1181	1210	1156	1153	1432	1432
MMLWU	0.09485	0.09406	0.06400	0.07257	0.10251	0.09880	0.06779	0.07154
MEAN LOG # WKS UNEMPLD PR YR 67-84	0.0031	0.0013	0.0282	0.0117	0.0005	0.0008	0.0104	0.0069
	968	1160	1176	1205	1151	1148	1427	1427
MNUMEMP	-0.05518	-0.06238	-0.10754	-0.00073	-0.02883	-0.02243	0.14294	0.13282
# DIFFT EMPLOYERS OVER YRS 67-84	0.0944	0.0374	0.0003	0.9804	0.3394	0.4581	0.0001	0.0001
	920	1114	1127	1151	1100	1097	1363	1363
MTURNOV	-0.02247	-0.04244	-0.08244	-0.03274	-0.01589	-0.01755	0.13467	0.13082
# JOB TURNOVERS OVER YRS 67-84	0.4960	0.1569	0.0056	0.2670	0.5986	0.5615	0.0001	0.0001
	920	1114	1127	1151	1100	1097	1363	1363

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
GMFINC	1137	8.65487205	0.73414347	MMFINC	1776	8.78442560	0.66527286
GMEARN	1351	7.65779527	0.92708343	MMEARN	1447	7.45301032	0.90764630
GMWAGE	1369	0.62971649	0.38441806	MMWAGE	1429	0.48068515	0.41305938
GMLHRWK	1410	3.49383313	0.40348531	MMLHRWK	1544	3.43528137	0.39868274
GMLWW	1339	3.51822565	0.62356326	MMLWW	1573	3.47699033	0.59614040
GMLWU	1336	1.23198659	0.24003852	MMLWU	1568	1.21755883	0.22433432
GNUMEMP	1670	2.87784431	1.62534602	MNUMEMP	1493	2.02545211	1.32642579
GTURNOV	1670	1.99401198	1.67130294	MTURNOV	1493	1.31480241	1.49306773

Table A8
Correlations Among Time Averages of
Selected Labor Market Variables of
Fathers and Mothers

Correlation
p-value
Sample Size

Mother's Variables	MMFINC	MMEARN	MMWAGE	MMLHRWK	MMLWW	MMLWU	MNUMEMP	MTURNOV
WMFINC	0.81738	0.66224	0.62235	0.12611	0.29904	0.27300	-0.01738	0.00029
MEAN FAMILY INCOME (IN LOGS)	0.0001	0.0001	0.0001	0.0247	0.0001	0.0001	0.7591	0.9959
	315	284	282	317	319	319	314	314
WMEARN	0.50645	0.30612	0.32577	-0.01964	0.10838	0.09368	0.05534	0.02026
MEAN INCOME FROM WG&SAL (IN LOGS)	0.0001	0.0001	0.0001	0.7592	0.0885	0.1413	0.3894	0.7528
	242	220	223	246	248	248	244	244
WMWAGE	0.59219	0.36570	0.44401	0.03377	0.03441	0.02763	0.01138	0.01510
MEAN HOURLY WAGE RATE (IN LOGS)	0.0001	0.0001	0.0001	0.6049	0.5965	0.6708	0.8622	0.8179
	232	210	214	237	239	239	235	235
WMLHRWK	0.16172	0.09284	0.05862	-0.00131	0.03044	0.00539	0.08523	0.07651
MEAN LOG # HRS WORKD PR WEEK 67-84	0.0091	0.1605	0.3721	0.9830	0.6205	0.9301	0.1682	0.2162
	259	230	234	264	267	267	263	263
WMLWW	0.19139	0.06477	0.04910	0.04714	0.09825	0.10087	-0.09350	-0.05371
MEAN LOG # WKS WORKD PR YEAR 67-84	0.0015	0.3177	0.4452	0.4354	0.0980	0.0927	0.1219	0.3749
	272	240	244	276	279	279	275	275
WMLWU	0.19942	0.08138	0.05655	0.06038	0.09801	0.09944	-0.09127	-0.06417
MEAN LOG # WKS UNEMPLD PR YR 67-84	0.0010	0.2100	0.3801	0.3184	0.1030	0.0980	0.1318	0.2899
	271	239	243	275	278	278	274	274
WNUMEMP	0.01282	-0.08195	-0.10685	0.04549	0.00541	0.02547	0.05193	0.05415
# DIFFT EMPLOYERS OVER YRS 67-84	0.8418	0.2293	0.1140	0.4731	0.9317	0.6862	0.4127	0.3929
	245	217	220	251	254	254	251	251
WTURNOV	-0.03012	-0.13003	-0.09544	0.08010	0.04539	0.05817	-0.00803	0.02155
# JOB TURNOVERS OVER YRS 67-84	0.6389	0.0558	0.1583	0.2060	0.4714	0.3559	0.8868	0.7341
	245	217	220	251	254	254	251	251

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
MMFINC	326	8.93863089	0.61288137	WMFINC	330	8.81367053	0.644725(
MMEARN	290	8.57478001	0.76237365	WMEARN	254	7.48377654	0.8787384(
MMWAGE	289	1.00016933	0.51173680	WMWAGE	246	0.47062167	0.41783621
MMLHRWK	331	3.75400070	0.26094121	WMLHRWK	274	3.41572747	0.4758601
MMLWW	334	3.82238799	0.25559933	WMLWW	287	3.52379513	0.5698201
MMLWU	334	1.33515478	0.08442340	WMLWU	286	1.23516459	0.20030076
MNUMEMP	328	1.35975610	1.09145805	WNUMEMP	260	1.86538462	1.333107
MTURNOV	328	0.71036585	1.19053962	WTURNOV	260	1.10384615	1.417208

Table A9
Correlations Among Time Averages of
Selected Labor Market Variables of
(Mature) Husbands and Wives

Correlation
p-value
Sample Size

	Husband's Variables							
Wife's Variables	MMFINC	MMEARN	MMWAGE	MMLHRWK	MMLWW	MMLWU	MNUMEMP	MTURNOV
WMFINC	0.83930	0.68117	0.64496	0.10651	0.25903	-0.21989	-0.02710	-0.02579
MEAN FAMILY INCOME (IN LOGS)	0.0001	0.0001	0.0001	0.0231	0.0001	0.0104	0.5663	0.5853
	460	405	398	455	456	135	450	450
WMEARN	0.48270	0.25930	0.22540	-0.01123	0.12076	-0.13967	0.00144	-0.01258
MEAN INCOME FROM WG&SAL (IN LOGS)	0.0001	0.0001	0.0001	0.8307	0.0208	0.1282	0.9783	0.8119
	364	327	329	365	366	120	360	360
WMWAGE	0.57124	0.36560	0.38304	0.02007	0.07856	-0.17331	-0.00222	0.00609
MEAN HOURLY WAGE RATE (IN LOGS)	0.0001	0.0001	0.0001	0.7079	0.1413	0.0594	0.9672	0.9102
	349	311	315	351	352	119	346	346
WMLHRWK	0.14453	0.04085	0.01185	-0.02435	0.01013	-0.04686	0.06836	0.05309
MEAN LOG # HRS WORKD PR WEEK 67-84	0.0045	0.4548	0.8279	0.6325	0.8421	0.6053	0.1819	0.3001
	385	337	339	388	389	124	383	383
WMLWW	0.21735	0.07789	0.05597	0.04715	0.13472	-0.00655	-0.08160	-0.03515
MEAN LOG # WKS WORKD PR YEAR 67-84	0.0001	0.1453	0.2943	0.3433	0.0065	0.9412	0.1027	0.4828
	404	351	353	406	407	129	401	401
WMLWU	0.05691	0.08630	0.04359	0.06955	0.10482	0.07840	-0.01802	-0.05742
MEAN LOG # WKS UNEMPLD PR YR 67-84	0.4531	0.2749	0.5818	0.3563	0.1626	0.5315	0.8129	0.4504
	176	162	162	178	179	66	175	175
WNUMEMP	-0.02852	-0.05297	-0.05143	-0.01265	-0.07003	0.00918	0.10281	0.09176
# DIFFT EMPLOYERS OVER YRS 67-84	0.5855	0.3457	0.3591	0.8078	0.1771	0.9214	0.0488	0.0787
	3[illegible]	319	320	372	373	118	368	368
WTURNOV	-0.07797	-0.10849	-0.07394	0.03373	-0.03409	0.01212	0.05922	0.08153
# JOB TURNOVERS OVER YRS 67-84	0.1355	0.0528	0.1871	0.5166	0.5115	0.8963	0.2572	0.1185
	368	319	320	372	373	118	368	368

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
MMFINC	479	8.98791268	0.62795181	WMFINC	468	8.04148753	0.63522996
MMEARN	415	8.63473459	0.72767959	WMEARN	370	7.49317685	0.93147168
MMWAGE	411	1.02739934	0.48223215	WMWAGE	357	0.50530654	0.42124986
MMLHRWK	479	3.75391816	0.24151169	WMLHRWK	394	3.40354360	0.48458471
MMLWW	480	3.83264548	0.25843802	WMLWW	413	3.56977447	0.58682125
MMLWU	141	2.09344488	0.96504691	WMLWU	180	2.01399324	1.06269132
MNUMEMP	472	1.33050847	1.08496840	WNUMEMP	377	1.81432361	1.23663348
MTURNOV	472	0.66101695	1.17634389	WTURNOV	377	1.05570292	1.34067925

Table A10
Correlations Among Time Averages of
Selected Labor Market Variables of
All Young Men

Correlation
p-value
Sample Size

Young Men's Variables	NMFINC	NMEARN	NMWAGE	NMLERWK	NMLWW	NMLWU	NNUMEMP	NTURNOV
NMFINC	1.00000	0.70589	0.63149	0.21001	0.26153	0.26505	-0.13085	-0.12281
MEAN FAMILY INCOME (IN LOGS)	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	3569	3505	3489	3530	3421	3421	3555	3555
NMEARN		1.00000	0.69732	0.27175	0.41878	0.45621	-0.11829	-0.13763
MEAN INCOME FROM WAG&SAL (IN LOGS)		0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
		4159	4085	4114	3948	3947	4149	4149
NMWAGE			1.00000	0.00081	0.15742	0.15354	-0.12961	-0.12249
MEAN HOURLY WAGE RATE (IN LOGS)			0.0000	0.9584	0.0001	0.0001	0.0001	0.0001
			4138	4121	3925	3924	4130	4130
NMLERWK				1.00000	0.21221	0.23684	-0.06495	-0.00666
MEAN LOG # ERS WORKD PR WEEK 67-81				0.0000	0.0001	0.0001	0.0001	0.6654
				4222	4011	4010	4214	4214
NMLWW					1.00000	0.74635	-0.08585	-0.07762
MEAN LOG # WKS WORKD PR YEAR 66-80					0.0000	0.0001	0.0001	0.0001
					4044	4043	4034	4034
NMLWU						1.00000	-0.06177	-0.05102
MEAN LOG # WKS UNEMPLD PR YR 66-80						0.0000	0.0001	0.0012
						4043	4033	4033
NNUMEMP							1.00000	0.93883
# DIFFT EMPLOYERS OVER YRS 66-81							0.0000	0.0001
							5061	5061
NTURNOV								1.00000
# JOB TURNOVERS OVER YRS 66-81								0.0000
								5061

VARIABLE	N	MEAN	STD DEV
NMFINC	3569	8.83757547	0.38202651
NMEARN	4159	8.56414998	0.67382711
NMWAGE	4138	1.09868604	0.41951552
NMLERWK	4222	3.75894319	0.19425772
NMLWW	4044	3.72485852	0.41597247
NMLWU	4043	1.33131336	0.10052530
NNUMEMP	5061	3.28037937	1.84835905
NTURNOV	5061	2.84038728	2.01503758

Table A11
Correlations Among Time Averages of
Selected Labor Market Variables of
All Young Women

Correlation
p-value
Sample Size

Young Woman's Variables	GMFINC	GMEARN	GMWAGE	GMLHRWK	GMLWW	GMLWU	GNUMEMP	GTURNOV
GMFINC	1.00000	0.29979	0.42920	-0.03894	0.11022	0.12296	-0.01751	0.00341
MEAN FAMILY INCOME (IN LOGS)	0.0000	0.0001	0.0001	0.0280	0.0001	0.0001	0.3181	0.8460
	3516	3136	3116	3186	3011	2965	3251	3251
GMEARN		1.00000	0.66858	0.46599	0.63255	0.38129	0.10084	0.09242
MEAN INCOME FROM WAG&SAL (IN LOGS)		0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
		3900	3802	3810	3633	3591	3798	3798
GMWAGE			1.00000	0.13141	0.33321	0.29793	0.05573	0.05808
MEAN HOURLY WAGE RATE (IN LOGS)			0.0000	0.0001	0.0001	0.0001	0.0006	0.0003
			3907	3843	3628	3580	3800	3800
GMLHRWK				1.00000	0.27787	0.24194	0.05750	0.02547
MEAN LOG # HRS WORKD PR WEEK 68-82				0.0000	0.0001	0.0001	0.0003	0.1103
				4034	3778	3727	3832	3832
GMLWW					1.00000	0.95364	0.10178	0.11375
MEAN LOG # WKS WORKD PR YEAR 68-82					0.0000	0.0001	0.0001	0.0001
					3786	3737	3707	3707
GMLWU						1.00000	0.09616	0.10576
MEAN LOG # WKS UNEMPLD PR YR 69-82						0.0000	0.0001	0.0001
						3737	3663	3663
GNUMEMP							1.00000	0.84823
# DIFFT EMPLOYERS OVER YRS 68-82							0.0000	0.0001
							4608	4608
GTURNOV								1.00000
# JOB TURNOVERS OVER YRS 68-82								0.0000
								4608

VARIABLE	N	MEAN	STD DEV
GMFINC	3516	8.72745257	0.69030869
GMEARN	3900	7.62515006	0.93963328
GMWAGE	3907	0.63527491	0.39472813
GMLHRWK	4034	3.46409443	0.42015345
GMLWW	3786	3.51067020	0.61610517
GMLWU	3737	1.23120530	0.23418210
GNUMEMP	4608	2.73220486	1.60010994
GTURNOV	4608	1.88650174	1.66291281

Table A12
Correlations Among Time Averages of
Selected Labor Market Variables of
All Older Men

Correlation
p-value
Sample Size

Older Men's Variables	MMFINC	MMEARN	MMWAGE	MMLHRWK	MMLWW	MMLWU	MNUMEMP	MTURNOV
MMFINC	1.00000	0.78363	0.75666	0.18396	0.31315	0.28064	-0.07515	-0.11214
MEAN TOT NET FAM INC <RETMNT (LOG)	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	4471	3737	3697	4284	4298	4296	4248	4248
MMEARN		1.00000	0.80191	0.19448	0.40255	0.37700	-0.09845	-0.16930
MEAN INC FRM WAG&SAL <RETMNT (LOG)		0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
		3800	3609	3784	3791	3781	3778	3778
MMWAGE			1.00000	0.00029	0.17061	0.15961	-0.10714	-0.09891
MEAN WAGE < RETIREMENT (LOG)			0.0000	0.9854	0.0001	0.0001	0.0001	0.0001
			3932	3882	3892	3890	3843	3843
MMLHRWK				1.00000	0.32859	0.30569	-0.09627	-0.02842
MEAN LOG # HRS WORKD PR WEEK 65-83				0.0000	0.0001	0.0001	0.0001	0.0564
				4753	4743	4741	4508	4508
MMLWW					1.00000	0.96415	-0.13869	-0.15275
MEAN LOG # WKS WORKD PR YEAR 65-83					0.0000	0.0001	0.0001	0.0001
					4779	4778	4532	4532
MMLWU						1.00000	-0.12605	-0.13762
MEAN LOG # WKS UNEMPLD PR YR 65-83						0.0000	0.0001	0.0001
						4778	4532	4532
MNUMEMP							1.00000	0.86083
# DIFFT EMPLOYERS OVER YRS 66-83							0.0000	0.0001
							4545	4545
MTURNOV								1.00000
# JOB TURNOVERS OVER YRS 66-83								0.0000
								4545

VARIABLE	N	MEAN	STD DEV
MMFINC	4471	8.86560349	0.71328544
MMEARN	3800	8.61582441	0.78093214
MMWAGE	3932	1.04399211	0.51982805
MMLHRWK	4753	3.74008359	0.26185557
MMLWW	4779	3.82287075	0.30841200
MMLWU	4778	1.33447226	0.10968131
MNUMEMP	4545	1.24598460	0.98726366
MTURNOV	4545	0.54543454	1.03661608

Table A13
Correlations Among Time Averages of
Selected Labor Market Variables of
All Mature Women

Correlation
p-value
Sample Size

Mature Women's Variables	WMFINC	WMEARN	WMWAGE	WMLERWK	WMLWW	WMLWU	WNUMEMP	WTURNOV
WMFINC	1.00000	0.38732	0.49766	0.45336	0.17228	0.16671	-0.13245	-0.11232
MEAN FAMILY INCOME (IN LOGS)	0.0000	0.0001	0.0001	0.0006	0.0001	0.0001	0.0001	0.0001
	4845	3877	3879	4121	4122	4110	3976	3976
WMEARN		1.00000	0.67654	0.54258	0.55966	0.52152	-0.05463	-0.08975
MEAN INCOME FROM WG&SAL (IN LOGS)		0.0000	0.0001	0.0001	0.0001	0.0001	0.0008	0.0001
		3974	3825	3908	3898	3893	3795	3795
WMWAGE			1.00000	0.21554	0.26296	0.23237	-0.13356	-0.13727
MEAN HOURLY WAGE RATE (IN LOGS)			0.0000	0.0001	0.0001	0.0001	0.0001	0.0001
			3996	3969	3908	3900	3803	3803
WMLERWK				1.00000	0.27064	0.25328	0.02938	0.00756
MEAN LOG # HRS WORKD PR WEEK 67-84				0.0000	0.0001	0.0001	0.0617	0.6307
				4264	4178	4168	4043	4043
WMLWW					1.00000	0.95615	0.01531	0.03001
MEAN LOG # WKS WORKD PR YEAR 67-84					0.0000	0.0001	0.3297	0.0560
					4284	4271	4058	4058
WMLWU						1.00000	0.02515	0.03301
MEAN LOG # WKS UNEMPLD PR YR 67-84						0.0000	0.1094	0.0356
						4271	4054	4054
WNUMEMP							1.00000	0.88254
# DIFFT EMPLOYERS OVER YRS 67-84							0.0000	0.0001
							4117	4117
WTURNOV								1.00000
# JOB TURNOVERS OVER YRS 67-84								0.0000
								4117

VARIABLE	N	MEAN	STD DEV
WMFINC	4845	8.82951597	0.67864982
WMEARN	3974	7.59787198	0.81572237
WMWAGE	3996	0.57062039	0.42618245
WMLERWK	4264	3.42414424	0.44408158
WMLWW	4284	3.51872849	0.57775924
WMLWU	4271	1.23344388	0.21461316
WNUMEMP	4117	2.01603109	1.26765904
WTURNOV	4117	1.28807384	1.52675717

Table A14

Correlations Among Time Averages of
Selected Labor Market Variables of
Young Men's Fathers and Young Men's Reports of Their Wives

Correlation
p-value
Sample Size

Young Men's Father's Variables

Report of Wife's Variables	MMFINC	MMEARN	MMWAGE	MMLERWK	MMLWW	MMLWU	MNUMEMP	MTURNOV
FMEARN	0.15584	0.12842	0.13590	0.04008	0.04042	0.02823	-0.03805	-0.02689
MEAN WIFE'S INC FRM WG&SAL 66-81	0.0001	0.0037	0.0023	0.3270	0.3217	0.4889	0.3575	0.5155
	588	509	500	600	603	603	587	587
FMLERWK	0.04936	0.00439	-0.03747	0.01580	-0.05875	-0.03143	0.04604	0.00230
WIFE MEAN LOG # ERS WKD/WK 78&81	0.3060	0.9328	0.4755	0.7410	0.2177	0.5098	0.3398	0.9619
	432	371	365	440	442	442	432	432
FMLWW	0.07387	0.00227	-0.00425	0.04877	0.03353	0.06343	0.04021	0.02824
WIFE MEAN LOG # WKS WRKD 66-81	0.0899	0.9815	0.9286	0.2574	0.4351	0.1396	0.3560	0.5168
	528	453	446	541	544	54.	529	529

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
MMFINC	1025	9.01926414	0.68495565	FMEARN	816	7.55834283	0.94164311
MMEARN	886	8.68951833	0.75226464	FMLERWK	452	3.47232147	0.41754866
MMWAGE	881	1.10229976	0.53071836	FMLWW	555	3.37012677	0.71273750
MMLERWK	1065	3.76518621	0.23241436				
MMLWW	1071	3.84279891	0.23937801				
MMLWU	1071	1.34028703	0.08778533				
MNUMEMP	1042	1.24588138	0.97672509				
MTURNOV	1042	0.56429942	1.00249062				

Table A15

Correlations Among Time Averages of

Selected Labor Market Variables of

Young Men's Mothers and Young Men's Reports of Their Wives

Correlation

p-value

Sample Size

	Young Men's Mother's Variables						
Report of Wife's Variables	WMFINC	WMEARN	WMAGE	WMLERWK	WMLWW	WMLWU	WNUMEMP	WTURNOV
FMEARN	0.12442	0.08187	0.08298	0.06384	0.08287	0.09810	-0.00181	-0.02612
MEAN WIFE'S INC FRM WG&SAL 66-81	0.0002	0.0149	0.0287	0.0759	0.0203	0.0072	0.9607	0.4781
	887	714	695	774	784	781	740	740
FMLERWK	-0.12600	-0.06568	-0.07648	0.05664	-0.05147	-0.04595	0.02866	0.01702
WIFE MEAN LOG @ HRS WKD/WK 78&81	0.0011	0.1253	0.0769	0.1705	0.2100	0.2639	0.4985	0.6878
	668	546	536	587	595	593	560	560
FMLWW	0.04614	0.06767	0.00529	0.08189	0.03755	0.04923	0.00496	-0.03058
WIFE MEAN LOG @ WKS WRKD 66-81	0.1795	0.0892	0.8957	0.0326	0.3229	0.1959	0.8990	0.4335
	779	632	617	681	695	692	658	658

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
WMFINC	1599	8.78165702	0.68421014	FMEARN	915	7.48278375	0.93354708
WMEARN	1258	7.44408290	0.94516679	FMLERWK	692	3.45566786	0.47247324
WMAGE	1244	0.48339998	0.40172855	FMLWW	809	3.38736305	0.71862711
WMLERWK	1373	3.40906255	0.45839787				
WMLWW	1392	3.48733496	0.62268848				
WMLWU	1388	1.21900723	0.24004305				
WNUMEMP	1296	1.92669753	1.37827497				
WTURNOV	1298	1.22530864	1.56757932				

Table A16

Correlations Among Time Averages of

Selected Labor Market Variables of

Young Women's Fathers and Young Women's Reports of Their Husbands

Correlation

p-value

Sample Size

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Young Woman's Father's Variables

Report of Husband's Variables	MMFINC	MMEARN	MMWAGE	MMLHRWK	MMLWW	MMLWU	MNUMEMP	MTURNOV
HMEARN	0.28740	0.32414	0.34355	0.05242	0.08719	0.08272	0.03653	-0.01924
MEAN HUSB'S INC FRM WG&SAL 68-82	0.0001	0.0001	0.0001	0.1770	0.0120	0.0327	0.3535	0.6252
	656	556	538	665	667	667	647	547
HMLHRWK	0.02947	-0.02986	0.02683	0.02581	-0.00650	-0.01329	-0.06213	-0.03204
HUSB MEAN LOG # HRS WKD/WK 68-78	0.4620	0.4923	0.5443	0.5146	0.8700	0.7378	0.1228	0.4266
	625	531	513	635	637	637	618	618
HMLWW	0.05343	0.02370	0.07262	-0.01552	-0.01541	-0.01789	-0.01238	-0.00519
HUSB MEAN LOG # WKS WRKD 69-78	0.1847	0.5882	0.1024	0.6981	0.6997	0.6525	0.7602	0.8981
	618	524	507	627	629	629	611	611
HMLWU	-0.07381	-0.09394	-0.06769	-0.09463	-0.01935	-0.00370	-0.00709	-0.02506
HUSB MEAN LOG # WKS UNEMPL75-82	0.3534	0.2840	0.4496	0.2281	0.8057	0.9625	0.9289	0.7523
	161	132	127	164	164	164	161	161

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
MMFINC	936	9.01979965	0.69072630	HMEARN	667	8.49821886	0.61884523
MMEARN	798	8.67935380	0.85776234	HMLHRWK	656	3.74117661	0.21724094
MMWAGE	786	1.08932343	0.56074908	HMLWW	648	3.81892393	0.25615698
MMLHRWK	958	3.75238655	0.29888395	HMLWU	168	2.32955111	0.91277616
MMLWW	963	3.82750698	0.28429812				
MMLWU	962	1.33716690	0.09162740				
MNUMEMP	837	1.24119530	1.00929963				
MTURNOV	837	0.59765208	1.08865303				

Table A17

Correlations Among Time Averages of

Selected Labor Market Variables of

Young Women's Mothers and Young Women's Reports of Husbands

Correlation

p-value

Sample Size

	Young Women's Mother's Variables							
Report of Husband's Variables	WMFINC	WMEARN	WMAGE	WMLERWK	WMLWW	WMLWU	WNUMEMP	WTURNOV
HMEARN	0.28650	0.16223	0.19969	0.05524	0.11604	0.09311	-0.08005	-0.05038
MEAN HUSB'S INC FRM WG&SAL 68-82	0.0001	0.0001	0.0001	0.0675	0.0001	0.0018	0.0089	0.1000
	1284	1035	1026	1096	1120	1117	1067	1067
HMLERWK	0.02936	0.02286	-0.01618	0.02686	0.00633	0.00760	0.03000	0.03632
HUSB MEAN LOG # ERS WKD/WK 68-78	0.3051	0.4735	0.6137	0.3855	0.8362	0.8041	0.3390	0.2470
	1222	985	976	1046	1069	1067	1018	1018
HMLWW	-0.01846	0.03124	0.01812	0.02087	0.06152	0.00591	0.03047	0.04088
HUSB MEAN LOG # WKS WKKD 69-78	0.5196	0.3283	0.5726	0.5011	0.0449	0.8477	0.3324	0.1934
	1219	981	972	1041	1063	1060	1014	1014
HMLWU	-0.15557	-0.07664	-0.09538	-0.02681	-0.05952	-0.06613	-0.05208	-0.02992
HUSB MEAN LOG # WKS UNEMPL75-82	0.0033	0.1916	0.1056	0.6451	0.2954	0.2457	0.3752	0.6106
	355	292	289	302	311	310	292	292

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
WMFINC	1778	8.78442560	0.66527286	HMEARN	1316	8.43606315	0.54481404
WMEARN	1447	7.45301032	0.90764630	HMLERWK	1259	3.74261147	0.19278883
WMAGE	1429	0.48068515	0.41305938	HMLWW	1252	3.81051199	0.26980594
WMLERWK	1544	3.43528137	0.39868274	HMLWU	363	2.23899812	0.98691519
WMLWW	1573	3.47699033	0.59614040				
WMLWU	1568	1.21755883	0.22433432				
WNUMEMP	1483	2.02545211	1.32642579				
WTURNOV	1483	1.31480241	1.49306773				

Table A18
Correlations Among Time Averages of Selected Labor Market Variables of Young Men and Their Reports of Their Wives

Correlation
p-value
Sample Size

Young Man's Variables

Report of Wife's Variables	NMFINC	NMEARN	NMWAGE	NMLERWK	NMLWW	NMLWU	NNUMEMP	NTURNOV
FMEARN	0.36621	0.15260	0.14185	0.01180	0.07406	0.06393	-0.04091	-0.05534
MEAN WIFE'S INC FRM WG&SAL 66-81	0.0001	0.0001	0.0001	0.5196	0.0001	0.0006	0.0219	0.0019
	2724	2939	2939	2978	2884	2863	3138	3138
FMLERWK	0.00252	-0.13987	-0.14216	-0.04862	-0.03972	-0.07441	0.07650	0.06889
WIFE MEAN LOG @ HRS WKD/WK 78&81	0.9099	0.0001	0.0001	0.0229	0.0665	0.0006	0.0003	0.0012
	2021	2149	2149	2189	2135	2134	2208	2208
FMLWW	0.16173	0.01089	-0.00321	-0.00967	0.07234	0.04685	-0.01578	-0.02906
WIFE MEAN LOG @ WKS WRKD 66-81	0.0001	0.5702	0.8670	0.6105	0.0002	0.0150	0.3968	0.1186
	2535	2720	2728	2775	2694	2693	2886	2886

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
NMFINC	3569	8.93757547	0.58202651	FMEARN	3142	7.46703941	0.90689986
NMEARN	4159	8.56414998	0.67382711	FMLERWK	2208	3.43212593	0.49126587
NMWAGE	4138	1.09868604	0.41951552	FMLWW	2889	3.33500203	0.73393962
NMLERWK	4222	3.75894319	0.18425772				
NMLWW	4044	3.72495852	0.41597247				
NMLWU	4043	1.33131336	0.10052530				
NNUMEMP	5061	3.28037837	1.84835905				
NTURNOV	5061	2.84038728	2.01503758				

Table A19
Correlations Among Time Averages of Selected Labor Market Variables of Young Women and Their Reports of Their Husbands

Correlation
p-value
Sample Size

Young Women's Variables

Report of Husband's Variables	GMFINC	GMEARN	GMWAGE	GMLHRWK	GMLWW	GMLWU	GNUMEMP	GTURNOV
HMEARN	0.53460	0.12546	0.26483	-0.08418	0.00955	0.01983	-0.00831	-0.00764
MEAN HUSB'S INC FRM WG&SAL 68-82	0.0001	0.0001	0.0001	0.0001	0.5933	0.2711	0.6207	0.6493
	2967	3209	3206	3305	3128	3083	3546	3546
HMLHRWK	0.09500	-0.06093	-0.05495	-0.01604	-0.02916	-0.01246	-0.04962	-0.01600
HUSB MEAN LOG # HRS WKD/WK 68-78	0.0001	0.0007	0.0022	0.3627	0.1080	0.4954	0.0035	0.3473
	2899	3113	3115	3221	3039	2994	3453	3453
HMLWW	0.18824	0.00053	-0.00647	-0.01369	0.01677	0.02395	-0.04360	-0.03734
HUSB MEAN LOG # WKS WRKD 69-78	0.0001	0.9764	0.7191	0.4386	0.3560	0.1906	0.0108	0.0289
	2877	3096	3096	3204	3031	2987	3422	3422
HMLWU	-0.16524	-0.02665	-0.05800	0.04067	0.00579	0.00278	-0.03018	-0.01649
HUSB MEAN LOG # WKS UNEMPL75-82	0.0001	0.4223	0.0790	0.2133	0.8617	0.9336	0.3510	0.6104
	849	909	918	938	907	904	957	957

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
GMFINC	3518	8.72745257	0.69030869	HMEARN	3865	8.48934328	0.57330051
GMEARN	3900	7.62515006	0.93963328	HMLHRWK	3774	3.75272962	0.19251187
GMWAGE	3907	0.53527491	0.39472813	HMLWW	3714	3.82161931	0.25649797
GMLHRWK	4034	3.46409443	0.42015345	HMLWU	1028	2.24607506	0.94750436
GMLWW	3786	3.51067020	0.61610517				
GMLWU	3737	1.23120530	0.23418210				
GNUMEMP	4608	2.73220486	1.60010994				
GTURNOV	4608	1.88650174	1.66291281				

Table A20
Correlations Among Time Averages of
Selected Labor Market Variables of
Young Women and Their Brothers' Reports of Their Wives

Correlation
p-value
Sample Size

	Young Woman's Variables							
Brother's Report of Wife's Variables	GMFINC	GMEARN	GMWAGE	GMLHRWK	GMLWW	GMLWU	GNUMEMP	GTURNOV
FMEARN	0.10114	0.12612	0.12045	-0.01137	0.09748	0.07985	0.03363	0.04968
MEAN WIFE"S INC FRM WG&SAL 66-81	0.0068	0.0003	0.0006	0.7422	0.0056	0.0235	0.2981	0.1242
	716	814	805	840	807	803	959	959
FMLHRWK	-0.03761	-0.01297	-0.06759	0.08843	0.00748	0.00544	-0.05259	-0.04947
WIFE MEAN LOG # HRS WKD/WK 78&81	0.3817	0.7468	0.0924	0.0245	0.8524	0.8924	0.1604	0.1867
	543	622	621	647	621	620	714	714
FMLWW	0.09485	0.10919	0.04699	0.06418	0.08279	0.05730	0.00795	0.01462
WIFE MEAN LOG # WKS WRKD 66-81	0.0174	0.0032	0.2057	0.0778	0.0257	0.1235	0.8172	0.6708
	639	729	727	756	726	724	848	848

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
GMFINC	1252	8.63047396	0.74604271	FMEARN	1034	7.50009065	0.91646079
GMEARN	1437	7.62984918	0.93478365	FMLHRWK	758	3.44316001	0.45315254
GMWAGE	1435	0.61805095	0.39022845	FMLWW	907	3.35039103	0.76464565
GMLHRWK	1493	3.49014277	0.39140119				
GMLWW	1402	3.50751262	0.62570340				
GMLWU	1394	1.22812330	0.24330012				
GNUMEMP	1732	2.74769053	1.61677028				
GTURNOV	1732	1.86836028	1.66278916				

Table A21
Correlations Among Time Averages of Selected Labor Market Variables of Young Men and Their Sisters' Reports of Their Husbands

Correlation
p-value
Sample Size

Young Men's Variables

Sister's Report of Husband's Variables	NMFINC	NMEARN	NMWAGE	NMLHRWK	NMLWW	NMLWU	NNUMEMP	NTURNOV
NMEARN	0.18719	0.17880	0.24157	0.03641	0.05450	0.05056	-0.02420	-0.01759
MEAN HUSB'S INC FRM WG&SAL 68-82	0.0001	0.0001	0.0001	0.2342	0.0834	0.1085	0.3844	0.5274
	878	1057	1048	1069	1010	1009	1294	1294
NMLHRWK	0.02546	0.07247	0.09018	0.01544	0.06475	0.07383	-0.03866	-0.03447
HUSB MEAN LOG # HRS WKD/WK 68-78	0.4595	0.0208	0.0040	0.6197	0.0430	0.0211	0.1712	0.2226
	846	1018	1016	1036	977	976	1254	1254
NMLWW	0.01739	0.01594	0.02156	-0.03030	0.06964	0.07066	0.05205	0.04852
HUSB MEAN LOG # WKS WRKD 69-78	0.6131	0.6115	0.4927	0.3302	0.0295	0.0273	0.0658	0.0864
	848	1018	1015	1035	977	976	1250	1250
NMLWU	-0.01078	-0.00168	-0.02032	-0.08937	-0.06436	-0.08180	-0.10049	-0.12122
HUSB MEAN LOG # WKS UNEMPL75-82	0.8598	0.9763	0.7176	0.1078	0.2524	0.1462	0.0509	0.0184
	271	317	319	325	318	317	378	378

VARIABLE	N	MEAN	STD DEV	VARIABLE	N	MEAN	STD DEV
NMFINC	1215	8.83289187	0.64938507	NMEARN	1317	8.41259160	0.57789372
NMEARN	1497	8.44208755	0.71940052	NMLHRWK	1278	3.73869074	0.19622481
NMWAGE	1486	1.02901971	0.43941944	NMLWW	1274	3.79343839	0.28551931
NMLHRWK	1516	3.73979589	0.20765965	NMLWU	380	2.37504770	0.91987827
NMLWW	1422	3.69584603	0.43254518				
NMLWU	1421	1.32219729	0.10829522				
NNUMEMP	1872	3.39155983	1.85497535				
NTURNOV	1872	2.71420940	1.98202802				

Table A22

Family Covariances (and Correlations) Among the Permanent Components of Log Real Earnings, Log Real Wage Rates, and Log Annual Hours Using Method of Moments Estimators

Young Men

	Log Earnings	Log Wages	Log Hours
Themselves			
Log earnings	.2430 (1.0000) N=36630	.1555 (.8582) N=35057	.0365 (.4523) N=17390
Log wages	--	.1351 (1.0000) N=33468	.0103 (.1712) N=19180
Log hours	--	--	.0268 (1.0000) N=8922
Brothers			
Log earnings	.0853 (.3510) N=6966	.0658 (.3632) N=6505	.0127 (.1574) N=3754
Log wages	--	.0562 (.4160) N=6157	.0045 (.0748) N=3507
Log hours	--	--	.0091 (.3396) N=2166
Sisters			
Log earnings	.0881 (.2913) N=15629	.0689 (.3055) N=14841	-.0021 (-.0209) N=8868
Log wages	.0576 (.3570) N=15661	.0498 (.4140) N=14878	-.0009 (-.0168) N=8865
Log hours	-.0008 (-.0037) N=7794	-.0145 (-.0889) N=7376	.0008 (.0110) N=4415

(continued)

Table A22--Continued

	Log Earnings	Log Wages	Log Hours
Fathers			
Log earnings	.1060	.0812	.0005
	(.3931)	(.4039)	(.0056)
	N-13143	N-12518	N-7231
Log wages	.0709	.0670	.0060
	(.3251)	(.4121)	(.0828)
	N-10539	N-10063	N-5751
Log hours	.0135	.0056	.0068
	(.1502)	(.0836)	(.2278)
	N-12333	N-11694	N-6828
Mothers			
Log earnings	.0863	.0707	.0061
	(.2855)	(.3136)	(.0608)
	N-15960	N-15070	N-9290
Log wages	.0511	.0454	.0034
	(.2997)	(.3572)	(.0601)
	N-19466	N-18422	N-11321
Log hours	.0373	.0216	.0044
	(.1959)	(.1521)	(.0696)
	N-13684	N-12893	N-8003

Table A23

Family Covariances (and Correlations) Among the Permanent Components of Log Real Earnings, Log Real Wage Rates, and Log Annual Hours Using Method of Moments Estimators

Young Women

	Log Earnings	Log Wages	Log Hours
Themselves			
Log earnings	.3764 (1.0000) N=18067	.1449 (.7217) N=17626	.2865 (1.0524) N=7967
Log wages	--	.1071 (1.0000) N=17742	.0190 (.1308) N=10036
Log hours	--	--	.1969 (1.0000) N=3464
Sisters			
Log earnings	.0970 (.2577) N=4276	.0562 (.2799) N=4300	.0367 (.1348) N=2141
Log wages	--	.0421 (.3931) N=4417	.0031 (.0213) N=2187
Log hours	--	--	.0542 (.2753) N=1102
Brothers			
Log earnings	.0881 (.2913) N=15629	.0576 (.3570) N=15661	-.0008 (-.0037) N=7794
Log wages	.0689 (.3055) N=14841	.0498 (.4140) N=14878	-.0145 (-.0889) N=7376
Log hours	-.0021 (-.0209) N=8868	-.0009 (-.0168) N=8865	.0008 (.0110) N=4415

(continued)

Table A23--Continued

	Log Earnings	Log Wages	Log Hours
Fathers			
Log earnings	.1329	.0867	.0228
	(.3960)	(.4843)	(.0939)
	N-9536	N-9591	N-4744
Log wages	.0762	.0545	-.0039
	(.2808)	(.3765)	(-.0199)
	N-7292	N-7353	N-3594
Log hours	.0118	.0049	.0001
	(.1055)	(.0821)	(.0012)
	N-8852	N-8883	N-4409
Mothers			
Log earnings	.1027	.0543	.0553
	(.2730)	(.2706)	(.2032)
	N-17717	N-18008	N-5877
Log wages	.0617	.0398	.0138
	(.2908)	(.3517)	(.0899)
	N-21550	N-21953	N-7142
Log hours	.0562	.0242	.0408
	(.2372)	(.1914)	(.2380)
	N-15093	N-15293	N-5016

Table A24

Family Covariances (and Correlations) Among the Permanent Components of Log Real Earnings, Log Real Wage Rates, and Log Annual Hours Using Method of Moments Estimators

Older Men

	Log Earnings	Log Wages	Log Hours
Themselves			
Log earnings	.2992 (1.0000) N=6417	.1999 (.8261) N=4610	.0365 (.3659) N=6109
Log wages	--	.1957 (1.0000) N=3487	.0002 (.0025) N=2417
Log hours	--	--	.0333 (1.0000) N=3485
Sons			
Log earnings	.1060 (.3931) N=13143	.0709 (.3251) N=10539	.0135 (.1502) N=12333
Log wages	.0812 (.4039) N=12518	.0670 (.4121) N=10063	.0056 (.0836) N=11694
Log hours	.0005 (.0056) N=7231	.0060 (.0828) N=5751	.0068 (.2278) N=6828
Daughters			
Log earnings	.1329 (.3960) N=9536	.0762 (.2808) N=7292	.0118 (.1055) N=8852
Log wages	.0867 (.4843) N=9591	.0545 (.3765) N=7353	.0049 (.0821) N=8883
Log hours	.0228 (.0939) N=4744	-.0039 (-.0199) N=3594	.0001 (.0012) N=4409

(continued)

Table A24--Continued

	Log Earnings	Log Wages	Log Hours
Wives			
Log earnings	.1142	.0738	.0143
	(.3404)	(.2720)	(.1279)
	N=5313	N=4298	N=4700
Log wages	.0688	.0532	.0115
	(.3637)	(.3477)	(.1824)
	N=6411	N=5227	N=5690
Log hours	.0312	.0161	.0183
	(.1477)	(.0942)	(.2598)
	N=4320	N=3511	N=3907

Table A25

Family Covariances (and Correlations) Among the Permanent Components of Log Real Earnings, Log Real Wage Rates, and Log Annual Hours Using Method of Moments Estimators

Mature Women

	Log Earnings	Log Wages	Log Hours
Themselves			
Log earnings	.3761 (1.0000) N-18284	.1753 (.8265) N-17645	.1906 (.8046) N-11893
Log wages	--	.1196 (1.0000) N-27304	.0521 (.3900) N-17564
Log hours	--	--	.1492 (1.0000) N-11593
Sons			
Log earnings	.0863 (.2855) N-15960	.0511 (.2997) N-19466	.0373 (.1959) N-13684
Log wages	.0707 (.3136) N-15070	.0454 (.3572) N-18422	.0216 (.1521) N-12893
Log hours	.0061 (.0608) N-9290	.0034 (.0601) N-11321	.0044 (.0696) N-8003
Daughters			
Log earnings	.1027 (.2730) N-17717	.0617 (.2908) N-21550	.0562 (.2372) N-15093
Log wages	.0543 (.2706) N-18008	.0398 (.3517) N-21953	.0242 (.1914) N-15293
Log hours	.0553 (.2032) N-5877	.0138 (.0899) N-7142	.0408 (.2380) N-5016

(continued)

Table A25--Continued

	Log Earnings	Log Wages	Log Hours
Husbands			
Log earnings	.1142	.0688	.0312
	(.3404)	(.3637)	(.1477)
	N-5313	N-6411	N-4320
Log wages	.0738	.0532	.0161
	(.2720)	(.3477)	(.0942)
	N-4298	N-5227	N-3511
Log hours	.0143	.0115	.0183
	(.1279)	(.1824)	(.2598)
	N-4700	N-5690	N-3907

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Chapter 2

An Intergenerational Model of Wages, Hours and Earnings

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Introduction

The degree to which economic success depends upon who one's parents happen to be and on the family environment in which one grows up is one of the fundamental questions in research on income distribution. Many studies have examined the intergenerational and sibling correlations among variables such as education, income, occupation, and socioeconomic status.[1] Studies such as Griliches (1979), and Hauser and Sewell (1986) have investigated the channels through which parental variables such as IQ, income, and education affect the cognitive ability, educational aspirations and attainment, and economic success of children. These and a number of studies by Taubman and others use data on identical and fraternal twins to examine the role of genetic and environmental factors in education and earnings. And a large number of studies use regression approaches to examine the effects of parental income and education on children's education and economic outcomes. Much of the discussion has focussed on (1) the size of the linkages in family income and education among siblings and across generations, and (2) the extent

1. See, for example, Corcoran and Jencks (1979), and studies summarized in Becker and Tomes (1986). Recent examples are Solon et al (1987) and Solon (1989).

to which the linkages reflect (a) genetic factors, (b) other influences on parents that in turn affect the development of their children, and (c) neighborhood and community influences on children that operate independently of the immediate family.[2]

In contrast to the large literature on family income, few studies have investigated family relationships in work hours, or examined the relative importance of family links in wages and in work hours in intergenerational and intragenerational correlations in income. It is common to say that an individual is from a family of "hard workers," but the question of whether leisure preferences are correlated among family members has received little study. Are there in fact similarities in work hours of family members? Do these similarities reflect labor supply responses to similarities in wages or to similarities in preferences? Are the wage rates and work preferences of young men and young women influenced primarily by fathers, mothers, or by characteristics of the family environment that are unrelated to the wages and labor supply preferences of the parents? To what extent does the correlation between the labor market outcomes of fathers and sons arise because of a direct effect of the father's characteristics on the son, and to what extent do they arise because of the process of assortative mating affects the characteristics of the mother which then directly influence the son's labor market outcome?

This paper is a first attempt at measuring the effects of parental and

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2. Individuals choose where to live, and so the characteristics of the neighborhood in which children are raised are not independent of the parents' characteristics. See Jencks and Mayer (forthcoming) for a recent survey of the effects of neighborhood characteristics on a variety of social outcomes. They cite only a few studies which have examined the effects of neighborhood characteristics on future earnings and family income; a recent one is Corcoran et al (1989).

"sibling" wage and work preference factors on the wages, hours, and earnings of young men and young women. We use intergenerational panel data from the National Longitudinal Surveys of Labor Market Experience to estimate a model of labor earnings of young men and young women. The two key components of the model are a factor model of wage rates, and a labor supply model. To be more precise, wages of young men and young women depend on the permanent component of the father's wage, the permanent component of the mother's wage, an unobserved sibling component representing background characteristics that are common to siblings but independent of the parents' factors, and an unobserved factor that is specific to each individual. Work hours depend on wages as well as labor supply preferences. Labor supply preferences of young men and young women depend on the father's preferences, the mother's preferences, a preference factor that is common to siblings, and an idiosyncratic preference factor. Finally, earnings depend upon wages and hours. Since we are particularly interested in gender differences in the determination of wages, earnings, and hours, most of the coefficients of the equations are gender specific. Since the underlying variables driving preferences, wages, hours, and earnings are unobserved, the model is a factor model.

The model is estimated from autocovariances and cross-covariances of hours, wages, and earnings for the young men and young women, and their fathers, mothers, and siblings who can be identified in the data sets. As we show, the model may be used to investigate the extent to which the parental and family characteristics that drive wage rates and work hours independently of wage rates are responsible for similarities among family members in labor market outcomes. In particular, we can distinguish among links in hours worked and earnings that reflect similarity in wages, and links that reflect

similar preferences; the linkages can be broken down further into similarities that are due to the father's characteristics and to the mother's characteristics. We use the model to decompose the variances of wages, work hours, and earnings of young men, young women, fathers, and mothers, and the covariances of these variables for the various parent-child and sibling pairs. The decomposition allows us to measure the relative contributions of the wage factors and work preference factors of the father and the mother to each of the estimated variances and covariances.

The paper proceeds as follows. In section I we present the factor model of earnings, hours, wage rates and preferences. We also discuss our approach to estimating the model and how the model can be used to decompose the variances of labor market outcomes of young men and young women and the covariances across family members into parental, sibling, and idiosyncratic factors that determine wage rates and work hours independently of wage rates. In section II we provide a brief discussion of the data and estimation issues. In section III we discuss the model estimates of the preference, wage, hours, and earnings equations. In section IV, we present the variance and covariance decompositions. We discuss the implications of the results and a research agenda in section V.

I. A Factor Model of Preferences, Wages, Hours and Earnings

In this section we specify a factor model of the permanent components of earnings, hours, and wage rates which dominate differences across individuals in lifetime income. Our basic approach is to specify equations relating the wages and work preferences of young men and women to unobserved parental factors, "sibling" factors that are common to children from the same family

but are uncorrelated with the parental factors, and individual specific factors. We also specify labor supply equations for young men and women and mature men and women that relate work hours to wages and to work preferences. Finally, we specify that earnings depend on wages and work hours, and make a set of assumptions about the covariances between the various unobserved factors in the model. We then discuss how the model may be used to analyze the sources of variation in labor market outcomes and how the model may be estimated.

I.1 Labor Supply Equations

The labor supply equations for young women, young men, mature women, and older men have the following form:

$$(1)\quad H_{ik} = \beta_k W_{ik} + U_{ik}$$

$$(2)\quad H_{ikt} = H_{ik} + e_{ikt}$$

where

- i - family indicator,
- k - person type , where k= b for young men (sons), g for young women (daughters), f for mature men (fathers) and m for mature women (mothers),
- t - year indicator,
- H_{ik} - the permanent value of the log of annual hours worked by person ik,
- H_{ikt} - log of <u>measured</u> annual hours worked by person ik in year t,
- W_{ik} - permanent wage of person ik,
- U_{ik} - permanent component of hours preferences of ik, and
- e_{ikt} - transitory determinants of hours and measurement error.

Since there may be more than one son and/or more than one daughter in family i, it is understood that subscript k is indexed by the person number j. However, we leave this index implicit except for when it is needed for clarity.

We refer to U_{ik} as the preference component of hours; for simplicity, we have normalized its coefficient to unity. The life cycle model of labor supply suggests that this interpretation of U_{ik} in (1) is an oversimplification. From the point of view of that model, β_k is the response of labor supply to a shift upward in the entire profile of lifetime wages. The term U_{ik} consists of the effects of preferences for goods and leisure on the marginal utility of lifetime income, and the direct effect of leisure preferences on labor supply. Later we will introduce the assumption that bequests and family transfers other than human capital investments of parents in children are unimportant. In this case similarities across family members in parental wealth should not produce large covariances in the marginal utility of incomes of relatives once we control for similarities in the permanent wage rates. However, if bequests and tranfers are important, then our interpretation of U_{ik} as "hours preferences" is incorrect, and, perhaps more importantly, the assumption made below that $Cov(U_{ik}, W_{ik'})=0$ for k= g or b, and k'= m or f would be unlikely to hold; that is, parents' wages may influence children's preferences for working.[3]

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3. The available evidence in Altonji, Hayashi and Kotlikoff (1989) and the papers that they cite suggests that altruistic links between parents and their adult children are relatively weak, and that transfers are a small component of income.

I.2 Earnings Equations

The permanent component of log earnings, E_{ik}, depends upon the log permanent wage, W_{ik}, and the log permanent hours level, H_{ik}, as given in (2); the observed earnings for person ik, E_{ikt}, includes a term capturing transitory influences and measurement error, ϵ_{ikt}:

$$(3) \quad E_{ikt} = \phi_{kw} W_{ik} + \phi_{kh} H_{ik} + \epsilon_{ikt}$$

After substituting (1) into (3) the log earnings equation is

$$(4) \quad E_{ikt} = [\phi_{kw} + \phi_{kh} * \beta_k] W_{ik} + \phi_{kh} U_{ik} + \epsilon_{ikt}$$

Note that the permanent wage component, W_{ik}, and the permanent preference component, U_{ik}, alone determine earnings and hours. Consequently, family linkages in earnings, hours, and wages are determined by family links in W_{ik} and in U_{ik}, which we now specify.

I.3 Family Links in Wages

In equations (5a, 5b) we specify that the permanent wages W_{ig} and W_{ib} of young women and men are determined by the permanent wages of their fathers and mothers, a family specific (or sibling) factor that is independent of the parental wage components, and an idiosyncratic factor:

$$(5a) \quad W_{ig} = a_{gf} W_{if} + a_{gm} W_{im} + a_{gs} \omega_{is} + \omega_{ig}$$

$$(5b) \quad W_{ib} = a_{bf} W_{if} + a_{bm} W_{im} + a_{bs} \omega_{is} + \omega_{ib}$$

where

W_{if} = father's permanent wage component,

W_{im} = mother's permanent wage (or potential wage if not working),

ω_{is} = common genetic or environmental factors that affect wages of children from family i independent of W_{if} and W_{im} -- we refer to this as the sibling factor, and

ω_{ik} = idiosyncratic component affecting a particular young man (k= b) or young woman (k= g) from household i.

We assume that the observed wage rate W_{ikt} is equal to the permanent wage W_{ik} plus an MA(2) error component, v_{ikt}, representing transitory factors and measurement error:

$$(6)\quad W_{ikt} = W_{ik} + v_{ikt} \qquad \text{for k= b, g, f, and m.}$$

I.4 Family Links In Preferences

Our factor model for children's preferences U_{ib} and U_{ig} has the same form as the model for their wages. Specifically,

$$(7a)\quad U_{ig} = \lambda_{gf} U_{if} + \lambda_{gm} U_{im} + \lambda_{gs} u_{is} + u_{ig}$$

$$(7b)\quad U_{ib} = \lambda_{bf} U_{if} + \lambda_{bm} U_{im} + \lambda_{bs} u_{is} + u_{ib}$$

where

U_{if} = father's permanent preference component,

U_{im} = mother's permanent preference component,

u_{is} = common genetic or environmental factors that affect work preferences of children from family i independent of U_{if} and U_{im} -- we refer to u_{is} as the sibling preference factor, and

u_{ik} = idiosyncratic preference component affecting a particular young man (k= b) or young woman (k= g) from household i.

The models for the wage and preference factors are flexible enough to

allow for differences between young men and young women in the influences of mothers and fathers and other common family characteristics.

I.5 Relationships Among the Wage and Preference Factors

Our assumptions about the preference factors U_{if}, U_{im}, u_{is}, u_{ib}, u_{ig}, and the wage factors W_{if}, W_{im}, ω_{is}, ω_{ib}, and ω_{ig} are as follows. First, we assume that they all are unrelated to the transitory components in hours, earnings, and wages: e_{ikt}, ϵ_{ikt}, and v_{ikt}. Next, we assume that covariances within the set of preference factors, and within the set of wage factors are zero, except for the parents' covariance of preferences, $Cov(U_{if}, U_{im})$, and covariance of wages, $Cov(W_{if}, W_{im})$. (These two covariances will be estimated in the model.) The key assumption, which will be discussed momentarily, is that all the preference factors are uncorrelated with all the wage factors.

We define ω_{is} to capture the sibling covariance in permanent wages remaining after both parents' wage influences are identified. Then any residual variation in wages is attributed to the idiosyncratic component ω_{ib} (or ω_{ig}) which is orthogonal to ω_{is} by construction; additionally, the individual components, ω_{ib} and ω_{ig}, are uncorrelated across all siblings. One can always perform such a decomposition, although ω_{is}, ω_{ig}, and ω_{ib} have clean interpretations as family influences and person specific influences only if there are no interaction effects between common family influences and person specific influences.[4] Similar remarks apply to the preference factors u_{is},

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[4]. The family factor ω_{is} may be a function of a large number of characteristics. One can summarize the influence of these characteristics with one factor provided that the function does not depend on the idiosyncratic characteristics of a particular young man or young women. Otherwise, ω_{is}, ω_{ig} and ω_{ib} provide a statistical decomposition of the set of interdependent family and person specific variables into a component that is common to siblings and one that is specific to the individual, while ignoring

u_{ib}, and u_{ig}.

Without additional indicators for preferences or components of the wage rate, it is necessary to make an identifying assumption about the relationship between preferences and the permanent wage rate. Our assumption that preferences are independent of the wage determinants is a particularly convenient one. It is also in line with standard practice in the male labor supply literature, which assumes that wages are unrelated to preferences once one controls for a small number of demographic variables that typically explain very little of the variance in work hours.[5] However, one might argue that leisure preferences have a direct effect on study time in elementary school, high school and college, as well as hours worked per year once one enters the labor market-- all of which may influence wage rates. Also, joint models of labor supply and human capital investment predict a positive relationship between schooling, on-the-job training, and preferences for market work.[6]

Special problems arise in the case of women, because hours of market work

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any interaction effects. For example, if the effect of neighborhood characteristics on the log permanent wage depends upon the IQ of the individual, then the dissimilarity of wage rates of brothers who have different IQs will change as one changes the neighborhood characteristics.

5. See Pencavel (1986). Some studies use instruments to control for preferences, but we do not find discussions of why particular variables, such as schooling, are exogenous to be particularly convincing. The use of instruments is also motivated as a means of reducing problems associated with measurement error in earnings divided by hours or to deal with missing data on wages for those who work zero hours.

6. With employee-financed on-the-job training, wage rates at a particular point in time underestimate productivity. We use a cubic specification in age to adjust our measures of earnings, hours, and wages for this possibility, and to eliminate any covariance between preferences and wages that might be associated with changes in preferences and wages over the lifecycle.

are a poor measure of the total labor supply of married women with children. Variables (such as attitudes toward raising children) that influence the allocation of time between market and nonmarket work are likely to influence the amount of time devoted to job training and the type of schooling that women select.[7] In future work, it would be interesting to add measures of nonmarket work (such as housekeeping and child care) to the hours of paid employment.[8]

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[7]. See Mincer and Polachek (1974), Polachek (1978) and Blakemore and Low (1981). For an opposing view emphasizing the role of discrimination, see England (1982).

[8]. Out of 1848 mother-daughter pairs, 296 are lost because the daughter dropped out of the sample before age 24 and/or before leaving school. The log work hours, age at the start of the sample, and education of the mother and daughter in the remaining 1552 cases that are potentially eligible for inclusion in the analysis are as follows.

		Daughter			Mother		
Sample:	% of Cases	Age in 68	Education	Log Hours	Age in 68	Education	Log Hours
Both Mother and Daughter Worked at Least Once	59.8	17.2	13.0	7.11	41.0	10.5	6.96
Mother Worked, Daughter Did Not	22.2	16.9	12.1	-	40.8	10.4	6.95
Daughter Worked, Mother Did Not	11.7	17.3	12.7	7.08	42.7	9.6	-
Neither Mother Nor Daughter Worked	6.3	17.1	11.6	-	41.6	9.6	-

The unconditional probability that a daughter does not work is .285. The probability that a daughter does not work conditional on the mother not working is .350. The means of log hours of mothers and of daughters are not very sensitive to whether or not the other works. The fact that the education levels are lower for those who do not work than for those who do is consistent with the positive labor supply elasticities we obtain. We do not wish to push these summary statistics too far, but they provide at least some suggestion that dealing with labor force participation will not

I.6 Assumptions About the Transitory Components of Wages, Hours, and Earnings

We assume the transitory components in wages, hours and earnings (v_{ikt}, e_{ikt}, and ϵ_{ikt}) are uncorrelated across different extended families i and across individuals within the same family. That is, the transitory components are uncorrelated across all individuals.[9] Formally,

$$(8) \qquad Cov(x_{ik(j)t}, z_{i'k'(j')t'}) = 0 \quad \text{if } ik(j) \neq i'k'(j'); \; x,z = v, \epsilon, e.$$

We assume that the autocovariances and cross covariances of e_{ikt}, ϵ_{ikt}, and v_{ikt} over time for a given individual are zero for observations that are more than two years apart. Formally,

$$(9) \qquad Cov(x_{ik(j)t}, z_{ik(j)t'}) = 0 \quad \text{if } |t - t'| > 2; \; x,z = v, \epsilon, e.$$

As in Chapter 1, we are ignoring any persistent shocks to earnings, hours, and wages that occur during a career.

I.7 Some Limitations of the Model

In this paper we deal with non-participation in the labor market by

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dramatically change our conclusions.

9. This assumption could fail to the extent that relatives are in the same industry, occupation or region, and that shifts in these variables are important for wage and hours determination. In such a case, the covariances among family members' variables would probably be overstated. However, we believe the bias is likely to be small, both because we suspect industry, occupation, and regional factors are unimportant relative to job specific and person specific factors, and because most of pairs of year specific observations for the relatives that are used to compute the covariances are drawn from different years.

excluding observations in which an individual did not work from the analysis. Individuals who never work are excluded entirely. Unfortunately, we do not have wage data for such individuals. Furthermore, limited dependent variables techniques (which would allow us to remedy this problem) are very difficult to handle in models with a large number of unobserved factors. Consequently, we leave this extension to future research while recognizing its potential importance.

The model is also restrictive in the treatment of family labor supply. First, we have already mentioned that we ignore altruistic linkages among relatives that would imply cross substitution effects of wage rates on hours of work. We do not view this as a serious misspecification. A larger concern is that we also exclude the spouse's wage for those individuals who are married, which means that we are treating the labor supply of husbands and wives as separate decisions. Since the evidence in Chapter 1 indicates that their wages are positively correlated, this omission could lead to biases, for example, in our estimated labor supply elasticities. We hope to relax this assumption in future work by constructing separate labor supply equations for married and unmarried individuals. However, to analyze other linkages among extended family members-- for example, between fathers and sons-in-law-- it will be necessary to add equations relating marital status and the expected value of the permanent wage and hours preferences of the husband to the parental, family, and idiosyncratic factors of the young woman. This complicates matters considerably, and so we feel that it is preferable to start our investigation with the simpler model presented here.

I.8 Fitting the Model and Variance Decompositions

The parameters of the model described above consist of the coefficients in the preference, wage, hours, and earnings equations, the variances of the wage and preference factors, and the covariances of wage and preference factors of the parents. These parameters determine the variances and covariances among the labor market outcomes of young men and young women as well as covariances between the labor market variables of children and parents, and among siblings. For example, equation (5b) implies that the covariance between the wages of brothers j and j' is

$$(10)\quad \mathrm{Cov}(W_{ib(j)}, W_{ib(j')}) = \mathrm{Cov}(W_{ib(j)t}, W_{ib(j')t'}) - a_{bf}^2\,\mathrm{Var}(W_{if}) + a_{bm}^2\,\mathrm{Var}(W_{im}) + 2a_{bm}\,a_{bf}\,\mathrm{Cov}(W_{if}, W_{im}) + a_{bs}^2\,\mathrm{Var}(\omega_{is}),$$

for $j \neq j'$, and for all t and t'.

The variance of young men's wages can be constructed from (5b) as follows

$$(11)\quad \mathrm{Var}(W_{ib(j)}) = \mathrm{Cov}(W_{ib(j)t}, W_{ib(j)t'}) - a_{bf}^2\,\mathrm{Var}(W_{if}) + a_{bm}^2\,\mathrm{Var}(W_{im}) + 2a_{bm}\,a_{bf}\,\mathrm{Cov}(W_{if}, W_{im}) + a_{bs}^2\,\mathrm{Var}(\omega_{is}) + \mathrm{Var}(\omega_{ib}), \quad |t - t'| > 2.$$

Equation (11) may be used to assess the contribution of the parental variables to the variance in the permanent wages of young men. The father's contribution is $a_{bf}^2\,\mathrm{Var}(W_{if})$ plus the portion of the covariance term $2a_{bm}\,a_{bf}\,\mathrm{Cov}(W_{if}, W_{im})$ that is assigned to the father. The contributions of the mother's wage, W_{im}, the family factor, ω_{is}, and the idiosyncratic factor, ω_{ib}, to the variance of the wages of young men are clearly laid out in the equation. The contributions of the various components to the brothers' wage

covariance (equation 10) are the same as the contributions to the young men's variance, except that the idiosyncratic factor ω_{ib} which is uncorrelated across brothers, plays a role in (11) but not in (10). Below we plug the estimated parameter values into formulae similar to (10) and (11) for other key variance and covariances,[10] and measure the contributions of the various wage and preference factors to the estimated variances and covariances.

I.9 Estimation

The parameters of the model are estimated by fitting the theoretical variances and covariances implied by equations (2), (4), (5), (6) and (7) to the sample estimates of the corresponding variances and covariances. There are 90 unique theoretical autocovariances and cross-covariances and sample moments.[11]

The procedure used to estimate the sample variances and covariances was discussed in Chapter 1, where it was referred to as the method of moments procedure; we repeat the discussion here. We compute family <u>covariances</u> of a particular labor market outcome by first adjusting the data to have zero mean, then computing the unique set of crossproducts of the elements of the vector of labor market outcomes in different years for one family member with the elements of the vector of labor market outcomes of the other family

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10. As another example, using equation (4), the covariance of daughters' and fathers' earnings is given by
$Cov(E_{ig}, E_{if}) = [\phi_{gw} + \phi_{gh}\beta_g][\phi_{fw} + \phi_{fh}\beta_f]Cov(W_{ig},W_{if}) + [\phi_{gh}\phi_{fh}]Cov(U_{ig},U_{if})$.

11. In Appendix Tables A1- A4 we present the sample estimates of the 90 unique variances and covariances of key variables and the corresponding correlation coefficients and sample sizes. For brevity's sake, we do not discuss them in the text, although many of the family covariances were discussed in Chapter 1.

member, and taking the mean of all the crossproducts for all of the pairs of family members. We estimate the variance of the permanent component of labor market outcomes for say, young men, by first computing the crossproducts of all unique pairs of yearly observations on a labor market outcome that are for the same individual and that are separated by more than two years in time and then taking the average of all of the crossproducts for all individuals.[12] We do the same for young women's, mature women's, and older men's variables.

The specific formulae for the method of moments covariances, variances, and correlations are as follows. Let $Y_{ik(j)t}$ be the adjusted[13] labor market outcome of an individual, where i denotes a set of related individuals, k is the type of individual (e.g., young man, young woman, older man, or mature woman) and j is an index indicating the specific individual of type k from family i. (The index j may exceed 1 when k refers to young men or young women and there is more than one young man or young woman from a given family.) The index t is a time subscript. Then the method of moments estimator of the covariance of variable Y with variable Z for family pair of type k,k' is

$$(12)\quad Cov(Y_{ik},Z_{ik'}) = \sum_i \left(\sum_j \sum_{j'} \sum_t \sum_{t'} Y_{ik(j)t}\, Z_{ik'(j')t'}\right) / N_{YZkk'}$$

When k= k', as is the case for brother pairs and for sister pairs, then the covariance estimator when Z = Y is

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12. If a labor market variable such as the wage rate is equal to a fixed component and a transitory component that can be represented by a moving average process of order 2 or less, then the transitory component will not bias our variance estimates.

13. We work with the residuals from a regression of each of the labor market outcomes against a cubic in age and a set of year dummies.

$$(13)\quad \mathrm{Cov}(Y_{ik(j)}, Z_{ik(j')}) = \sum_i \Big(\sum_j \sum_{j' \geq j} \sum_t \sum_{t'} Y_{ik(j)t}\, Z_{ik(j')t'}\Big) / N_{YYkk}$$

and when $Z \neq Y$ the covariance estimator is

$$(14)\quad \mathrm{Cov}(Y_{ik(j)}, Z_{ik(j')}) = \sum_i \Big(\sum_j \sum_{j' \neq j} \sum_t \sum_{t'} Y_{ik(j)t}\, Z_{ik(j')t'}\Big) / N_{YZkk}$$

The method of moments <u>variance</u> estimator for the variable Y for person type k is

$$(15)\quad \mathrm{Var}(Y_{ik(j)}) = \sum_i \Big(\sum_j \sum_t \sum_{t'>t+2} Y_{ik(j)t}\, Y_{ik(j)t'}\Big) / N_{Yk}$$

And the method of moments <u>covariance</u> estimator for the variables Y and Z for person type k is

$$(16)\quad \mathrm{Cov}(Y_{ik(j)}, Z_{ik(j)}) = \sum_i \Big(\sum_j \sum_t \sum_{\substack{t'>t+2 \\ t'<t-2}} Y_{ik(j)t}\, Z_{ik(j)t'}\Big) / N_{YZk}$$

In the above equations $N_{YZkk'}$, N_{YYkk}, N_{YZkk}, N_{Yk}, and N_{YZk} are the number of terms in the sums taken in (12), (13), (14), (15), and (16) respectively.

We point out in Chapter 1 that the samples used in estimation differ substantially for the different sample moments. That is, we use unbalanced data in estimating the model. This is necessitated by the fact that particular families i do not supply observations to all of the matched samples on family members, and not all of those individuals who are matched provide the same number of valid reports. We assume that the model parameters are the same for all families and in particular are not related to patterns of data availability. If this homogeneity assumption is false, then our model's

estimates of the family linkages will be biased.[14]

We fit the theoretical model to the sample moments by minimizing the discrepancy between a given sample moment and the corresponding prediction of the model. We estimate the model using both ordinary least squares (OLS) and weighted least squares (WLS), but we discuss only the WLS estimates. The OLS estimation assumes that the sampling errors in the 90 sample moments are uncorrelated and homoscedastic. In fact, they are likely to be heteroscedastic for two reasons. First, the underlying distributions of wages, hours, and earnings are not all the same, and any differences in the distributions will affect the precision of the estimated covariances and variances. Second, as mentioned earlier, the sample moments are estimated using different numbers of observations. To remedy the potential inefficiency in the parameter estimates caused by the differences in the precision of the estimated moments, the WLS procedure is implemented in which each observation corresponding to one of the 90 sample moments is weighted by the estimate of its sampling variance.

In estimating the variances of the sample moments it is necessary to take account of the fact that individual crossproducts that enter the sums in (12) through (16) are <u>not</u> independent within each family i. We account for this by expressing each sample covariance as the sum of the sums of individual crossproducts contributed by each family i. The sums for a particular family i are the terms in brackets in (12), (13), (14) and (15). The sums in brackets are independent across families under our assumptions, and (after dividing by the average number of crossproducts per family) have an

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14. Moderately large balanced samples can be generated using the Panel Study of Income Dynamics, and it would be useful to compare estimates of our model based on balanced and unbalanced PSID samples.

expectation (taken across families) equal to the particular covariance. It is then easy to formulate a consistent estimator of the variance of the sample covariance. For example, consider the covariance estimator in (12). One may rewrite $Cov(Y_{ik},Z_{ik'})$ as

$$Cov(Y_{ik},Z_{ik'}) = [1/I_{YZkk'}] \sum_i S_i$$

where $S_i = (\sum_j \sum_{j'} \sum_t \sum_{t'} Y_{ik(j)t} Z_{ik'(j')t'}) (I_{YZkk'}/N_{YZkk'})$

and $I_{YZkk'}$ is the number of different families contributing observations on variables Y and Z for persons of type k and k'. One may think of the S_i as independent and identically distributed random variables drawn from a distribution over all families. The expectation of S_i over this distribution is $Cov(Y_{ik}, Z_{ik'})$. It follows that a consistent estimator of the sampling variance of $Cov(Y_{ik},Z_{ik'})$ is

$$Var[(Cov(Y_{ik},Z_{ik'})] = \sum_i [S_i - Cov(Y_{ik},Z_{ik'})]^2 / I_{YZkk'}$$

It should be pointed out that neither the OLS standard errors nor the WLS standard errors account for correlation in the sampling errors across different sample moments.[15]

II. Data

The data used in this analysis are from the four Original Cohorts of the

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15. We have chosen not to use a full GLS estimator that would account for correlation in the sampling errors of the sample moments because of the difficulties in getting good estimates of the correlations among the sample moments when the sample is highly unbalanced.

National Longitudinal Surveys of Labor Market Experience.[16] Specifically, we work with the sample of Young Men who were 14 to 24 years old in 1966 and were followed through 1981, the samples of Young Women who were 14 to 24 in 1968 and Mature Women who were 30 to 44 years old in 1967 and continue to be followed, and the sample of Older Men who were 45 to 59 in 1966 and were last surveyed in 1983. We use data through 1982 in the case of the young women and through 1984 in the case of mature women. Some of the households contributed more than one person to the young men and young women surveys, and in some cases the households contributed to both the youth surveys and older men and mature women surveys. Consequently, it is possible to match data on sibling pairs and parent-child pairs. The Appendix to Chapter 1 summarizes information on the sample sizes of the original cohorts, the number of siblings of each sex, the numbers of brother, sister, and brother-sister pairs, and the number of parent-child pairs.[17]

We take advantage of the panel nature of the data sets and use as many of the yearly reports as possible for each individual, subject to the following selection rules. The data for a particular variable may be missing either because the individual left the sample prior to that year's survey or because the response is missing or invalid for other reasons. In the case of the young men and young women we restrict the sample to individuals who were at least 24 years old prior to leaving the survey. We chose this age cutoff to reduce the influence of transitory variation in labor market outcomes

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16. Most of this data description is presented in Chapter 1. We repeat it here to make this chapter self-contained.

17. In Chapter 1 we discuss the possibility that the very fact that it is possible to match data across NLS cohorts may lead to biases in the estimates of the family linkages.

associated with the transition between school and work. We use labor market data (wages, annual hours, and earnings) from a particular year only if the individual was at least 24 and was out of school and did not return to school in a subsequent year.

The fact that many of the older men in the sample approach retirement age during the course of the survey raises additional complications. Earnings, work hours, and wage rates of such individuals after retirement may not be closely related to the typical or "permanent" values for these individuals over the course of their careers. To minimize this problem, we only use data on the labor market variables for individuals who had not yet retired, and who were less than 61 years old when the data were collected. Since the age in 1966 of the older men ranges from 45 to 59, there is substantial variance across sample members in the number of years of labor market data available. Retirement is not a concern for the mature women's sample through the years we study.

For all four cohorts we excluded wage observations of less than $.40 per hour, and earnings of less than $100 per year (both in 1967 dollars). Also, only annual hours (constructed as reported number of weeks worked times reported number of hours worked per week) greater than zero and less than 5000 hours were counted.

III. Estimates of Preference, Wages, Hours, and Earnings Equations

We begin with a discussion of the parameter estimates and the overall fit of the equations. We then turn in section IV to the analysis of sources of variation in wages, hours, and earnings.

Before turning to the results it is necessary to discuss a few

additional restrictions that are imposed upon the model's parameters prior to estimation. Without loss of generality we normalize the son's sibling wage factor parameter, a_{bs}, to unity. Consequently, the daughter's coefficient a_{gs} is the effect of the family wage factor ω_{is} on young women relative to the effect on young men. We also normalize both the son's and daughter's sibling preference factor coefficient, λ_{bs} and λ_{bg}, to unity. Models in which this restriction is relaxed are not empirically identified. For some of our models, we restricted the earnings equation parameters on wages and hours, ϕ_{kw} and ϕ_{kh} for all k, to unity on the grounds that both log hours and the log wage should have coefficients of 1 in an equation for log earnings. As will be shown below, relaxing these restrictions produces coefficients on wages and hours which are, for the most part, reasonably close to unity.

To save space, we will focus our discussion on the WLS results in Table 1 for the model that does <u>not</u> restrict ϕ_{kw} and ϕ_{kh} to unity. We choose to present this specification for two reasons. First, the parameter estimates are not that sensitive to the inclusion of the earnings equations restrictions, and the model without them is more general. Second, the WLS estimates are likely to be more efficient than the OLS estimates. For comparisons, Appendix Table A5 presents the <u>OLS</u> estimates for the model without the earnings equation restrictions, and Table A6 shows the WLS estimates <u>with</u> the restrictions on the wage and hours parameters in the earnings equations.

The equations for the preferences and wages of young men and young women are in the top two panels of Table 1. The father's preferences U_{if} have a coefficient of .215 with a standard error of .072 in the equation for U_{ib}, the young men's preferences. In the same equation, the mother's preferences have

a small negative coefficient which is statistically insignificant. Conversely, the father's preferences, U_{if}, have a negative but insignificant effect on the preferences of young women, while the mother's preferences have a coefficient (standard error) of .368 (.081). Apparently, parental influences on labor supply preferences depend upon gender, with the father playing a strong positive role for young men and the mother playing an even stronger positive role for young women.

The estimates of the standard deviations of the young men's and older men's preferences, $\sigma_{u_{ib}}$ and $\sigma_{U_{if}}$, are .142 and .179, respectively. The corresponding estimates for young women and mature women, $\sigma_{u_{ig}}$ and $\sigma_{U_{im}}$, are noticeably larger at .444 and .351. The covariance of the parents' preference factors is .016. Lastly, the sibling preference factor u_{is} has an estimated standard deviation of .066 and enters the preference equations with coefficients that have been normalized to unity; consequently, it plays an important role in the variation in preferences for both young men and young women.

The equations for the wages of young men (W_{ib}) and young women (W_{ig}) show strong and statistically significant effects of the parental factors. The coefficients (standard errors) on the father's and mother's wages, W_{if} and W_{im}, in the young men's wage equation are .280 (.033) and .258 (.037), respectively. The corresponding coefficients in the young women's wage equation are .282 and .209, both of which are significant. The family factor ω_{is} has a coefficient of .831 in the equation for W_{ig} with a standard error of .183. This estimate falls short of the corresponding coefficient of 1 in the young men's wage equation, but by less than one standard error; so there is no strong evidence that young women's wages are more sensitive than young

men's to common family factors that are independent of the parental wage factors. The idiosyncratic wage factors for young men, ω_{ib}, and for young women, ω_{ig}, have estimated standard deviations of .281 and .255, which are smaller than the standard deviations of the parents' wage factors: .424 for fathers and .345 for mothers. The parents' wage factors have an estimated covariance equal to .054 which is more than three times larger than the covariance of their preference factors.

The bottom left hand side panel of Table 1 reports the estimated labor supply equations. The labor supply elasticity estimates (standard errors) are .056 (.015) for young men, .077 (.027) for mature men, .184 (.045) for young women, and .445 (.043) for mature women. The small estimates for men are basically consistent with a large body of evidence. The results for young women are on the low side, but consistent with the conclusions of Mroz' (1987) study of static labor supply for married women. The estimate for the mature women is well within the wide range of estimates available for women, but larger than the estimates suggested by Mroz' work. Overall, these labor supply elasticities estimates seem reasonable.

The estimated coefficients on wages and hours in the earnings equations (ϕ_{kw} and ϕ_{kh}, k= b, g, f, and m) are close to unity in all cases except for the older men's hours coefficient which is found to be .551 with a standard error of .294. Not surprisingly then, the model's parameter estimates are not very sensitive to whether or not we restrict the wage and hours parameters to unity in the earnings equation. (Compare Table 1 to Table A6.)

The factor model, which has 33 free parameters, explains 99 percent of the variance of the unweighted sample moments. Since we do not know the covariances among the sampling errors in the 90 moments, it is not possible to

perform a formal test of the factor model as a description of the sample moments. However, if the covariances among the sampling errors are zero, then the weighted sum of squared errors of the model has a χ^2 distribution with (90-33-57) degrees of freedom; in fact, the model's weighted sum of squared errors is 35.10, which has a p-value of .99. Since the covariances are not independent, this goodness of fit test may be biased either for or against the factor model. In any case, we conclude that the parameter estimates are basically sensible, and that the model fits the family covariances well enough to be used to perform variance decompositions.[18]

IV. Decomposing the Variances and Covariances Among Labor Market Outcomes

Tables 2a, 2b, and 2c examine the contributions of each of the wage and preference factors to the variances of permanent wages, hours, and earnings of young men and young women, and to the covariances of these three variables among siblings and parent-child pairs. The decompositions presented in the tables are based on the parameter estimates in Table 1 which were found using

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18. In the OLS version of the model-- the results of which are reported in Table A5-- the estimated parental preference factors are quite different from the corresponding WLS estimates, but the estimated standard deviations of the preference factors are very close to the WLS estimates. The estimated wage factor coefficients and the estimated standard deviations of the wage factors are quite close to the WLS estimates reported in the text. The estimated labor supply elasticities in the OLS model are consistently smaller than the WLS estimates, especially the fathers'. Finally, the OLS hours and wage coefficients in the earnings equations are also quite close to the WLS estimates, except for the fathers' hours coefficient. Overall, as one would expect, the standard errors of the OLS parameter estimates are larger than the corresponding WLS standard errors.

In the WLS version of the model with the hours and wage coefficients restricted to unity (Table A6), the preference and wage factors are essentially the same as in the WLS version without the restrictions. Unsurprisingly, the labor supply elasticities in the restricted version are consistently larger than those in the unrestricted version. The restricted version has a "goodness of fit" p- value of .69.

WLS on the factor model which did not impose restrictions on the wage and hours parameters in the earnings equations. The first column of each row lists the particular covariance or variance that we are examining. For example, in the first row of the Table 2a we examine $Cov(W_{ib(j)},W_{ib(j')})$, the wage covariance of brothers. The sample estimates (derived using the method of moments approach described in section I.9) and the values predicted by the factor model for each of the moments are reported in the second and third columns. The actual and fitted values are .0562 and .0548 in the case of the brothers' wage covariance. Columns 4, 5 and 6 report the contribution of the father's wage factor, W_{if}, the mother's wage factor, W_{im}, and the combined contributions of both parents plus, $Cov(W_{if},W_{im})$, the covariance of their wage factors. The contribution of the sibling factor, ω_{is}, and contribution of the idiosyncratic factor ω_{ib} or ω_{ig} are shown in the seventh and eighth columns. Columns 9 through 13 report the corresponding contributions of the various preference factors.

The number in parentheses below each factor contribution is the fraction of the predicted value of the particular moment (column 3) that is due to the particular factor. For example, the results in Table 2a indicate that W_{if} is responsible for 26 percent of the covariance of brothers' wages and 11 percent of the variance of wages of young men (the second row of the table). The mother's wage contribution, W_{im}, is 14 percent of $Cov(W_{ib(j)},W_{ib(j')})$ and 6 percent of $Var(W_{ib(j)})$. The total contribution of the parents' wages-- the father's plus the mother's plus their covariance--is 54 percent of the covariance between brothers' wages, and 22 percent of the variance of young men's wages. The sibling wage factor accounts for 46 percent of the similarity between brothers and only 19 percent of the variance in the wages

of young men. Fifty-nine percent of the young men's wage variance is due to the idiosyncratic wage factor.

Given space limitations it is not possible to discuss the decompositions of each of the variances and covariances listed in the tables. Instead, we provide summaries of the main results for wages, hours, and earnings.

III.1 Wages (Table 2a)

The effects of parents' wage factors and siblings' wage factors are pretty much the same for different types of sibling pairs, although the combined parental wage factors are slightly more important relative to the sibling wage factors for sister pairs than for brother pairs or brother-sister pairs. To be precise, the parents' total contribution to the wage covariance of brothers is .029800 which constitutes 54 percent of the total covariance of brothers' wages; for brother- sister pairs, the parents contribute .027637, or 57 percent; and for sister pairs the contribution is .025756 or 60 percent. Sibling wage factors account for 46 percent of the covariance in brothers' wages, 43 percent of the brother-sister covariance, and only 40 percent of sisters' wage covariance.

Looking at the <u>variance</u> of wages, one sees that the father's wage factor and mother's wage factor explain 11 percent and 6 percent of the variance of young men's wages; however, since the two parental factors have a positive covariance, the total parents' contribution is 22 percent of the variance of young men's wages. The remaining variation in young men's wages is explained by the sibling wage factor which accounts for 19 percent and the idiosyncratic effect which explains 59 percent. For young women's wage variance, one sees a slightly larger parental contribution, 24 percent, and a slightly smaller

sibling effect, 16 percent, and an individual effect which claims 60 percent. That sibling wage effects are slightly weaker for young women and sister pairs than for young men and brother pairs is a reflection of the finding that the sibling factor coefficient in the young women's wage equation in Table 1 was estimated to be .831, while the young men's coefficient was normalized to unity.

The decompositions of the covariances of the wages of parents and children are particularly interesting. The results for young men in row 3 of Table 2a indicate that the father's factor, W_{if}, explains 78 percent of the father-son wage covariance. The rest is attributed to the fact that the father's wage factor is positively correlated with the mother's wage factor, and the mother's wage factor has a direct effect on the wage of the son.[19] The results for the father-daughter wage covariance are very similar, with W_{if} explaining 82 percent of the covariance (see row 7). The mother's wage factor, W_{im}, accounts for only 67 percent of the wage covariance between mothers and sons, and for 62 percent between mothers and daughters. The remainder is due to the fact that the mother's wage factor is positively correlated with the father's wage factor and the father's wage factor has a direct effect on the children's wages. An implication of these findings is that studies that simply look at, say, the correlation between fathers and sons' wages or incomes overstate the size of the direct link by attributing part of the mother's influence to the father.

One explanation for the larger role of the father's factor in the wages

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19. To appreciate the size of the parents' wage covariance, note that the sample covariance of the wages of fathers and mothers (in row 12 of Table 2a) is .0532, which is more than 25 percent of the variance of the fathers' wages (row 10) and almost half the variance of the mothers' wages (row 11).

of both young men and young women is that the wage rate may be a less accurate measure of the human capital of mothers than of fathers because of the large role women play in productive activity outside of the labor market.

III.2 Hours (Table 2b)

In view of the relatively small wage elasticities for young men and young women found in Table 1, it is not surprising that parental wage factors play only a small role in the variances of hours of young men (zero percent) and young women (1 percent) and in the covariances of hours of siblings.[20] The sibling wage factor also plays a relatively small role (in no case more than 5 percent) in these same moments. For brothers, the parental and sibling wage factors together explain only 3 percent of the variance in hours. For sisters, the parental wage factor explains 4 percent of the hours covariance and the sibling factor explains 3 percent. And for brother- sister pairs, the combined parents' and sibling wage effects explain 11 percent of the hours covariance.

The idiosyncratic components of wages also explain very little (1 percent) of the variation in the hours of young men and young women. For mature men the wage factor explains only 3 percent of their hours variance (row 10, column 4) leaving 97 percent of their hours variation explained by variation in their preferences. However, for older women, who have a larger estimated wage elasticity, variation in their wage factor, W_{im}, explains a much larger fraction, 16 percent, of the variation in their hours (row 11,

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20. It should be pointed out the model slightly underestimates the hours covariance of brothers and substantially underestimates the hours covariance of sisters. The model overestimates the hours covariance between brothers and sisters. Compare columns 2 and 3 in the first, fifth, and ninth rows.

column 5). Only 10 percent of the parents' hours covariance is attributable to their wage covariance. The remaining 90 percent is explained by the covariance of their preferences.

On the other hand, the parental and sibling hours preference factors make an important contribution to the variance in the hours of siblings, but there are large differences in the parental influences for males and females. The fathers' preference factor, U_{if}, contributes 25 percent of the covariance in brothers' hours, but only 5 percent of sisters' hours. At the same time, mothers' preferences account for essentially none of the brothers' or brothers-sisters' hours covariance, but a whopping 78 percent of sisters' hours covariance. Totalled, parental factors account for three times as much of the sisters' hours covariance than for the brothers'. The sibling preference factor explains 96 percent of the brother-sister hours covariance, 73 percent of the brothers', but only 20 percent of the sisters'.

A similar gender-specific pattern is seen in the hours variances of young men and young women. Fathers' preferences constitute the entire parental contribution for young men, and mothers' for young women. In both cases, the parental preference contribution to the hours variation is small, around 7 percent. The sibling factor u_{is} makes the same absolute contribution (.004410) to the variance of the hours of young women and of young men, but because young women have a much higher hours variance than young men (.1969 versus .0268) this contribution is only 2 percent of the young women's total versus 17 percent for young men. A large part of the difference in the variance of hours of young women and young men comes from the idiosyncratic factor, which has a variance of .197 (or 89 percent) for young women and only .020 (or 76 percent) for young men. The recurring pattern of relative roles

of the father's preferences and the mother's preferences for young men and brothers and for young women and sisters reflects the gender-specific pattern of the coefficients in the preference equations shown in the top panel of Table 1.

III.3 Earnings (Table 2c)

Examining the results in Table 2c, one can obtain specific answers to the question of the relative importance of wage factors and hours preference factors in determining the variances and covariances of earnings. With respect to the variances of earnings of young men (row 2), the parental wage factors explain 19 percent, the sibling wage factor explains 16 percent and the idiosyncratic wage factor explains 50 percent of the total variance. Combined, some 85 percent of the variance of earnings among young men is due to wage factors. The remaining 15 percent can be broken up as follows: the parental hours preferences contribute 1 percent of the variance in earnings, and the sibling factor and the idiosyncratic hours preference factors explain 2 percent and 12 percent, respectively.

For young women, the relative importance of wage differences and preference differences are reversed. In row 6, the parental, sibling and idiosyncratic wage factors contribute 11 percent, 7 percent and 26 percent, or a total of 44 percent, of the variance of E_{ig}. The parental, sibling, and idiosyncratic hours <u>preference</u> factors contribute 4 percent, 1 percent and 51 percent of the remaining variance in young women's earnings. For young women, the mother's hours preference factor explains 4 percent of the total variance, and 19 percent of the similarity between sisters (row 5), while the mother's contribution for young men and for brothers are essentially both zero.

The pattern of relative influences is similar across sibling pairs: about 50 percent of the covariation in earnings is due to parental wage factors and 40 percent to sibling wage factors. For brother and brother-sister pairs, parental preference factors are small relative to sibling factors; not so for sister pairs for whom mothers' preferences contribute 19 percent of the covariance in earnings.

In light of the wage and hours results reported above, it is not surprising to find that 75 percent of the covariance in the earnings of fathers and sons is due to the father's wage factor, while only 4 percent is due to the father's preference factor. The covariances of the earnings of sons and mothers, and daughters and fathers are also dominated by the parental wage factors. However, the mother's preference factor explains a relatively large 37 percent of the covariance of earnings between mothers and daughters (and zero percent between mothers and sons).

Finally, it is interesting to note that the variation in earnings of fathers is dominated by the wage factor, which explains 97 percent of the variance in row 10. For mothers (in row 11), the wage factor explains 71 percent of their earnings, although a substantial fraction-- 28 percent-- of the influence of the mothers' wage factor on mothers' earnings was found to operate through the labor supply response to wages.[21]

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21. This fraction was calculated as the ratio of the indirect influence of wages on earnings, which operates through the labor supply response of hours to wages, to the sum of the direct effect of wages on earnings plus the indirect effect. From equation (4) the reader can verify this ratio is $\phi_{hm}\beta_m/[\phi_{wm} + \phi_{hm}\beta_m]$, which equals .28 when the appropriate parameter values from Table 1 are substituted. For fathers, the labor response to wages accounts for 4 percent of the wage contribution to their earnings.

V. Summary and Conclusions

In this paper we have used a simple factor model to explore the sources of variation and of family similarities in wages, hours, and earnings. We have estimated the model using matched intergenerational and intragenerational panel data on labor market outcomes. The model consists of a simple static labor supply equation, an equation relating earnings to hours worked and wage rates, and factor models relating wage rates and hours preferences to parental, sibling, and idiosyncratic factors. Although many different pairs of individuals are used to compute the covariances and variances of earnings, wages, and hours that we seek to explain, our factor model performs well in explaining most of the variation in the sample moments. Furthermore, we obtain reasonable labor supply elasticities; also, the gender differences in the relative importance of work preferences and wage rates in the determination of work hours, and in the relative influence of fathers and mothers have some intuitive appeal. To our knowledge, we are the first to use intergenerational and sibling covariances in wage rates to identify labor supply elasticities.

Our main findings are as follows. First, the wages of both sons and daughters are quite responsive to the wage factors of fathers and mothers, with coefficients between .2 and .3 for our preferred specifications. The effect of the father is somewhat larger, particularly for daughters. However, the father's wage explains a substantially larger fraction of the total variance in wage rates, in part because the variation of the father's wage factor is substantially larger (by about one-third) than the variation in the mother's wage factor.

Second, the sibling wage factor and combined parents' factors explain

roughly the same percentages (45 percent and 55 percent) of the covariance of the wages of sibling pairs, no matter what type of sibling pair (brother-brother, sister-sister, or brother-sister) is considered. Furthermore, the relative contributions of fathers and mothers are the same for all sibling pairs, with the fathers' wage factor explaining twice as much of the sibling wage covariance as the mothers'.

We also document that intergenerational correlations substantially overestimate the direct influence of fathers, and especially mothers, on wages. A substantial part of the relationship between a parent and child arises because assortative mating induces a substantial positive covariance in the wage rates of the spouses (parents). We find, for example, that the covariance of the father's and mother's wages accounts for 22 percent of the covariance between father's and son's wages.

Without repeating our findings in detail, we should note that variation in hours <u>preferences</u> dominates the variation in wages in determining the permanent differences in hours among young men and young women. It is interesting to note, however, that 6 percent of the total variance is associated with parental preference factors and 17 percent is associated with the sibling preference factor in the case of young men. For young women only about 9 percent of the total variance is associated with parental <u>plus</u> sibling preference factors, the remainder is claimed by a large individual effect. The small influence of wage rates (particularly for young men, who have a low overall variation in hours), reflects the fact that our estimated labor supply elasticities are only .056 for young men and .184 for young women. For mature women (who have an estimated wage elasticity of .445), wage differences explain 16 percent of the total variance in hours, while for mature men, only

3 percent of the hours variance can be attributed to wage differences.

Our results for young men's earnings indicate that 85 percent of the variation is due to the wage factors and 15 percent to the hours preference factors; similarly, for mature men the figures are 97 percent and 3 percent. On the other hand, the hours preference factors are very important for the earnings of young women (claiming 56 percent), although almost all of the effect is accounted for by the idiosyncratic preference factor. For the mothers, 71 percent of the earnings variance is due to the wage factor, and 29 percent to the hours preference factor. Consequently, our decompositions of the earnings variances differ by gender, and by age in the case of women.

Most of the results that we have discussed are robust across the two specifications that we estimate and to the use of ordinary least squares rather than weighted least squares. However, we have highlighted a number of limitations of our model and methodology that will require further research. First, it would be useful to generalize the labor supply function to allow for parental wage effects on the children's marginal utility of income. Second, it would be useful to estimate labor supply models that depend upon marital status, which incorporate cross substitution effects of the spouse's wage. Third, and perhaps most important, it is important to address the problem of non- participation in the labor market.[22]

Fourth, our findings in Chapter 1 of strong covariances in wages, hours, and earnings between mothers and fathers and of substantial covariances in the

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22. We think that this is important not so much because we are concerned about selection bias in estimation of the labor supply elasticities, but because exclusion of data points in which individuals work zero hours probably has serious effects on our measures of the hours variances and covariances and on our estimates of the variances and covariances of leisure preferences.

earnings of "in-laws" suggests that it would be useful to extend the model to include equations relating the hours preference factors and wage factors of say, a young woman's husband to her wages and hours preferences, as well as to the wage and hours preferences of her siblings and parents. Of course, such an extension will require one to deal with the endogeneity of marriage. Finally, there are a host of econometric issues involving the use of unbalanced data that we have chosen to ignore and that could be explored in future research. The Panel Study of Income Dynamics provides larger samples of parents and children and siblings and more complete data on spouses than does the NLS. For this reason, it would be useful replicate our work with the PSID.

Table 1
WLS Estimates of Preference, Wage, Hours, and Earnings Equations

Preference Equations (6):

$$U_{ib} = \underset{(.072)}{.215}\, U_{if} - \underset{(.035)}{.008}\, U_{im} + u_{is} + u_{ib}$$

$$U_{ig} = \underset{(.195)}{-.178}\, U_{if} + \underset{(.081)}{.368}\, U_{im} + u_{is} + u_{ig}$$

$$\sigma_{u_{ib}} = \underset{(.010)}{.142} \qquad \sigma_{U_{if}} = \underset{(.011)}{.179} \qquad \sigma_{u_{is}} = \underset{(.018)}{.066}$$

$$\sigma_{u_{ig}} = \underset{(.017)}{.444} \qquad \sigma_{U_{im}} = \underset{(.016)}{.351} \qquad \mathrm{Cov}(U_{if},U_{im}) = \underset{(.007)}{.016}$$

Log Wage Equations (5):

$$W_{ib} = \underset{(.033)}{.280}\, W_{if} + \underset{(.037)}{.258}\, W_{im} + \omega_{is} + \omega_{ib}$$

$$W_{ig} = \underset{(.041)}{.282}\, W_{if} + \underset{(.040)}{.209}\, W_{im} + \underset{(.183)}{.831}\, \omega_{is} + \omega_{ig}$$

$$\sigma_{\omega_{ib}} = \underset{(.011)}{.281} \qquad \sigma_{W_{if}} = \underset{(.012)}{.424} \qquad \sigma_{\omega_{is}} = \underset{(.019)}{.158}$$

$$\sigma_{\omega_{ig}} = \underset{(.011)}{.255} \qquad \sigma_{W_{im}} = \underset{(.007)}{.345} \qquad \mathrm{Cov}(W_{if},W_{im}) = \underset{(.005)}{.054}$$

Log Hours Equations (2):

$$H_{ib} = \underset{(.015)}{.056}\, W_{ib} + U_{ib}$$

$$H_{ig} = \underset{(.045)}{.184}\, W_{ig} + U_{ig}$$

$$H_{if} = \underset{(.027)}{.077}\, W_{if} + U_{if}$$

$$H_{im} = \underset{(.043)}{.445}\, W_{im} + U_{im}$$

Log Earnings Equations (3):

$$E_{ib} = \underset{(.044)}{1.151}\, W_{ib} + \underset{(.161)}{1.172}\, H_{ib}$$

$$E_{ig} = \underset{(.081)}{1.089}\, W_{ig} + \underset{(.062)}{1.017}\, H_{ig}$$

$$E_{if} = \underset{(.066)}{1.120}\, W_{if} + \underset{(.294)}{.551}\, H_{if}$$

$$E_{im} = \underset{(.101)}{1.072}\, W_{im} + \underset{(.101)}{.933}\, H_{im}$$

Notes:
1. Standard errors are reported in parentheses.
2. The WLS regression producing these results had $R^2 = .99$, RMSE = .7847, Sum of Squared Errors = 35.10, and 57 degrees of freedom.
3. The p- value for the SSE drawn from a χ^2_{57} is .99.

Table 2a: Decomposition of Variances and Covariances

Moment	Sample Estimate[1]	Factor Model Prediction	Source of Variance: Wage Factors					Preference Factors				
			Father W_{if}	Mother W_{im}	Total Parents $W_{if}+W_{im}+Cov(W_f,W_m)$	Sibling ω_{is}	Individual ω_{ib} or ω_{ig}	Father U_{if}	Mother U_{im}	Total Parents $U_{if}+U_{im}+Cov(U_f,U_m)$	Sibling u_{is}	Individual u_{ib} or u_{ig}
$Cov(W_b,W_{b'})$	.0562	.0548	.014124 (.26)	.007918 (.14)	.029800 (.54)	.024967 (.46)	--					
$Cov(W_b,W_b)$	.1351	.1337	.014124 (.11)	.007918 (.06)	.029800 (.22)	.024967 (.19)	.078888 (.59)					
$Cov(W_b,W_f)$	.0670	.0642	.050378 (.78)	--	.064213 (1.00)	--	--					
$Cov(W_b,W_m)$	.0454	.0458	--	.030714 (.67)	.045761 (1.00)	--	--					
$Cov(W_g,W_{g'})$	.0421	.0430	.014270 (.33)	.005179 (.12)	.025756 (.60)	.017221 (.40)	--					
$Cov(W_g,W_g)$	.1071	.1081	.014270 (.13)	.005179 (.05)	.025756 (.24)	.017221 (.16)	.065127 (.60)					
$Cov(W_g,W_f)$	.0545	.0618	.050636 (.82)	--	.061827 (1.00)	--	--					
$Cov(W_g,W_m)$	.0398	.0400	--	.024841 (.62)	.039966 (1.00)	--	--					
$Cov(W_g,W_b)$	.0498	.0484	.014197 (.29)	.006404 (.13)	.027637 (.57)	.020735 (.43)	--					
$Cov(W_f,W_f)$	.1957	.1797	.179683 (1.00)	--	--	--	--					
$Cov(W_m,W_m)$	.1196	.1191	--	.119142 (1.00)	--	--	--					
$Cov(W_f,W_m)$	[illegible]	.0537	--	--	.053670 (1.00)	--	--					

(continued)

[1] Sample estimates of moments are drawn from Appendix Tables A1- A4: "Family Covariances (and Correlations) Among the Permanent Components . . . " Note that covariances of hours and wages, hours and earnings, and wages and earnings for the various family member pairs were also predicted by the Factor Model, but are not reported here.

Note: Numbers in parentheses are the fractions of the Factor Model Prediction attributable to the particular factors.

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Table 2b: Decomposition of Variances and Covariances--Continued

Moment	Sample Estimate[1]	Factor Model Prediction	Source of Variance: Wage Factors					Preference Factors				
			Father	Mother	Total Parents	Sibling	Individual	Father	Mother	Total Parents	Sibling	Individual
			W_{if}	W_{im}	$W_{if}+W_{im}+Cov(W_f,W_m)$	w_{is}	w_{ib} or w_{ig}	U_{if}	U_{im}	$U_{if}+U_{im}+Cov(U_f,U_m)$	u_{is}	u_{ib} or u_{ig}
$Cov(H_b,H_b')$	.0091	.0060	.000045 (.01)	.000025 (.00)	.000094 (.02)	.000079 (.01)	--	.001484 (.25)	.000009 (.00)	.001435 (.24)	.004410 (.73)	--
$Cov(H_b,H_b)$	.0268	.0264	.000045 (.00)	.000025 (.00)	.000094 (.00)	.000079 (.00)	.000249 (.01)	.001484 (.06)	.000009 (.00)	.001435 (.06)	.004410 (.17)	.020121 (.76)
$Cov(H_b,H_f)$	.0069	.0070	.000219 (.03)	--	.000279 (.04)	--	--	.006893 (.98)	--	.006758 (.96)	--	--
$Cov(H_b,H_m)$	.0044	.0036	--	.000767 (.21)	.001143 (.32)	--	--	--	-.001027 (-.29)	.002443 (.68)	--	--
$Cov(H_s,H_s')$	.0542	.0215	.000482 (.02)	.000175 (.01)	.000870 (.04)	.000581 (.03)	--	.001009 (.05)	.016731 (.78)	.015834 (.73)	.004410 (.20)	--
$Cov(H_s,H_s)$	.1969	.2210	.000482 (.00)	.000175 (.00)	.000870 (.01)	.000581 (.00)	.002199 (.01)	.001009 (.00)	.016731 (.08)	.015834 (.07)	.004410 (.02)	.197296 (.89)
$Cov(H_s,H_f)$	.0001	.0011	.000719 (.64)	--	.000877 (.78)	--	--	-.005683 (-5.04)	--	.000251 (.22)	--	--
$Cov(H_s,H_m)$	.0408	.0459	--	.002029 (.04)	.003265 (.07)	--	--	--	.045450 (.99)	.042588 (.93)	--	--
$Cov(H_s,H_b)$	.0008	.0046	.000147 (.03)	.000066 (.01)	.000285 (.06)	.000214 (.05)	--	-.001223 (-.27)	-.000378 (-.08)	-.000300 (-.07)	.004410 (.96)	--
$Cov(H_f,H_f)$	.0333	.0331	.001072 (.03)	--	--	--	--	.032020 (.97)	--	--	--	--
$Cov(H_m,H_m)$	.1492	.1470	--	.023543 (.16)	--	--	--	--	.123481 (.84)	--	--	--
$Cov(H_f,H_m)$	.0183	.0180	--	--	.001843 (.10)	--	--	--	--	.016120 (.90)	--	--

(continued)

[1] Sample estimates of moments are drawn from Appendix Tables A1- A4: "Family Covariances (and Correlations) Among the Permanent Components . . . " Note that covariances of hours and wages, hours and earnings, and wages and earnings for the various family member pairs were also predicted by the Factor Model, but are not reported here.

Note: Numbers in parentheses are the fractions of the Factor Model Prediction attributable to the particular factors.

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Table 2c: Decomposition of Variances and Covariances--Continued

Moment	Sample Estimate[1]	Factor Model Prediction	Source of Variance: Wage Factors — Father W_{if}	Mother W_{im}	Total Parents $W_{if}+W_{im}+Cov(W_f,W_m)$	Sibling w_{is}	Individual w_{ib} or w_{ig}	Preference Factors — Father U_{if}	Mother U_{im}	Total Parents $U_{if}+U_{im}+Cov(U_f,U_m)$	Sibling u_{is}	Individual u_{ib} or u_{ig}
$Cov(E_b,E_{b'})$	.0853	.0881	.020819 (.23)	.011726 (.13)	.044135 (.50)	.036977 (.41)	--	.002037 (.02)	.000012 (.00)	.001970 (.02)	.006056 (.07)	--
$Cov(E_b,E_b)$	.2430	.2336	.020819 (.09)	.011726 (.05)	.044135 (.19)	.036977 (.16)	.116836 (.50)	.002037 (.01)	.000012 (.00)	.001970 (.01)	.006056 (.02)	.027628 (.12)
$Cov(E_b,E_f)$	.1061	.1014	.076115 (.75)	--	.097019 (.96)	--	--	.004448 (.04)	--	.004362 (.04)	--	--
$Cov(E_b,E_m)$	.0863	.0855	--	.055573 (.65)	.082800 (.97)	--	--	--	-.001122 (-.01)	.002670 (.03)	--	--
$Cov(E_g,E_{g'})$	.0970	.0907	.023241 (.26)	.008435 (.09)	.041948 (.46)	.028047 (.31)	--	.001043 (.01)	.017305 (.19)	.016169 (.18)	.004561 (.05)	--
$Cov(E_g,E_g)$	.3764	.4009	.023241 (.06)	.008435 (.02)	.041948 (.11)	.028047 (.07)	.106070 (.26)	.001043 (.00)	.017305 (.04)	.016169 (.04)	.004561 (.01)	.204057 (.51)
$Cov(E_g,E_f)$	.1329	.0981	.080228 (.82)	--	.097958 (1.00)	--	--	--	-.003183 (-.03)	.000140 (.00)	--	--
$Cov(E_g,E_m)$	.1027	.1162	--	.047134 (.41)	.075833 (.65)	--	--	--	.043103 (.37)	.040389 (.35)	--	--
$Cov(E_g,E_b)$	.0881	.0800	.022049 (.2?	.009946 (.12)	.042923 (.54)	.032204 (.40)	--	-.001458 (-.02)	-.000450 (-.01)	-.000358 (-.00)	.005256 (.06)	--
$Cov(E_f,E_f)$	.2992	.2867	.276951 (.97)	--	--	--	--	.009712 (.03)	--	--	--	--
$Cov(E_m,E_m)$	.3761	.3707	--	.263371 (.71)	--	--	--	--	.107361 (.29)	--	--	--
$Cov(E_f,E_m)$	.1142	.1073	--	--	.099067 (.92)	--	--	--	--	.008279 (.08)	--	--

[1] Sample estimates of moments are drawn from Appendix Tables A1- A4: "Family Covariances (and Correlations) Among the Permanent Components . . ." Note that covariances of hours and wages, hours and earnings, and wages and earnings for the various family member pairs were also predicted by the Factor Model, but are not reported here.

Note: Numbers in parentheses are the fractions of the Factor Model Prediction attributable to the particular factors.

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Table A1

Family Covariances (and Correlations) Among the Permanent Components of Log Real Earnings, Log Real Wage Rates, and Log Annual Hours Using Method of Moments Estimators

Young Men

	Log Earnings	Log Wages	Log Hours
Themselves			
Log earnings	.2430 (1.0000) N=36630	.1555 (.8582) N=35057	.0365 (.4523) N=17390
Log wages	--	.1351 (1.0000) N=33468	.0103 (.1712) N=19180
Log hours	--	--	.0268 (1.0000) N=8922
Brothers			
Log earnings	.0853 (.3510) N=6966	.0658 (.3632) N=6505	.0127 (.1574) N=3754
Log wages	--	.0562 (.4160) N=6157	.0045 (.0748) N=3507
Log hours	--	--	.0091 (.3396) N=2166
Sisters			
Log earnings	.0881 (.2913) N=15629	.0689 (.3055) N=14841	-.0021 (-.0209) N=8868
Log wages	.0576 (.3570) N=15661	.0498 (.4140) N=14878	-.0009 (-.0168) N=8865
Log hours	-.0008 (-.0037) N=7794	-.0145 (-.0889) N=7376	.0008 (.0110) N=4415

(continued)

Table A1--Continued

	Log Earnings	Log Wages	Log Hours
Fathers			
Log earnings	.1060	.0812	.0005
	(.3931)	(.4039)	(.0056)
	N=13143	N=12518	N=7231
Log wages	.0709	.0670	.0060
	(.3251)	(.4121)	(.0828)
	N=10539	N=10053	N=5751
Log hours	.0135	.0056	.0068
	(.1502)	(.0836)	(.2278)
	N=12333	N=11694	N=6828
Mothers			
Log earnings	.0863	.0707	.0061
	(.2855)	(.3136)	(.0608)
	N=15960	N=15070	N=9290
Log wages	.0511	.0454	.0034
	(.2997)	(.3572)	(.0601)
	N=19466	N=18422	N=11321
Log hours	.0373	.0216	.0044
	(.1959)	(.1521)	(.0696)
	N=13684	N=12893	N=8003

Table A2

Family Covariances (and Correlations) Among the Permanent Components of Log Real Earnings, Log Real Wage Rates, and Log Annual Hours Using Method of Moments Estimators

Young Women

	Log Earnings	Log Wages	Log Hours
Themselves			
Log earnings	.3764 (1.0000) N=18067	.1449 (.7217) N=17626	.2865 (1.0524) N=7967
Log wages	--	.1071 (1.0000) N=17742	.0190 (.1308) N=10036
Log hours	--	--	.1969 (1.0000) N=3464
Sisters			
Log earnings	.0970 (.2577) N=4276	.0562 (.2799) N=4300	.0367 (.1348) N=2141
Log wages	--	.0421 (.3931) N=4417	.0031 (.0213) N=2187
Log hours	--	--	.0542 (.2753) N=1102
Brothers			
Log earnings	.0881 (.2913) N=15629	.0576 (.3570) N=15661	-.0008 (-.0037) N=7794
Log wages	.0689 (.3055) N=14841	.0498 (.4140) N=14878	-.0145 (-.0889) N=7376
Log hours	-.0021 (-.0209) N=8868	-.0009 (-.0168) N=8865	.0008 (.0110) N=4415

(continued)

Table A2--Continued

	Log Earnings	Log Wages	Log Hours
Fathers			
Log earnings	.1329	.0867	.0228
	(.3960)	(.4843)	(.0939)
	N-9536	N-9591	N-4744
Log wages	.0762	.0545	-.0039
	(.2808)	(.3765)	(-.0199)
	N-7292	N-7353	N-3594
Log hours	.0118	.0049	.0001
	(.1055)	(.0821)	(.0012)
	N-8852	N-8883	N-4409
Mothers			
Log earnings	.1027	.0543	.0553
	(.2730)	(.2706)	(.2032)
	N-17717	N-18008	N-5877
Log wages	.0617	.0398	.0138
	(.2908)	(.3517)	(.0899)
	N-21550	N-21953	N-7142
Log hours	.0562	.0242	.0408
	(.2372)	(.1914)	(.2380)
	N-15093	N-15293	N-5016

Table A3

Family Covariances (and Correlations) Among the Permanent Components of Log Real Earnings, Log Real Wage Rates, and Log Annual Hours Using Method of Moments Estimators

Older Men

	Log Earnings	Log Wages	Log Hours
Themselves			
Log earnings	.2992 (1.0000) N=6417	.1999 (.8261) N=4610	.0365 (.3659) N=6109
Log wages	--	.1957 (1.0000) N=3487	.0002 (.0025) N=2417
Log hours	--	--	.0333 (1.0000) N=3485
Sons			
Log earnings	.1060 (.3931) N=13143	.0709 (.3251) N=10539	.0135 (.1502) N=12333
Log wages	.0812 (.4039) N=12518	.0670 (.4121) N=10063	.0056 (.0836) N=11694
Log hours	.0005 (.0056) N=7231	.0060 (.0828) N=5751	.0068 (.2278) N=6828
Daughters			
Log earnings	.1329 (.3960) N=9536	.0762 (.2808) N=7292	.0118 (.1055) N=8852
Log wages	.0867 (.4843) N=9591	.0545 (.3765) N=7353	.0049 (.0821) N=8883
Log hours	.0228 (.0939) N=4744	-.0039 (-.0199) N=3594	.0001 (.0012) N=4409

(continued)

Table A3--Continued

	Log Earnings	Log Wages	Log Hours
Wives			
Log earnings	.1142	.0738	.0143
	(.3404)	(.2720)	(.1279)
	N-5313	N-4298	N-4700
Log wages	.0688	.0532	.0115
	(.3637)	(.3477)	(.1824)
	N-6411	N-5227	N-5690
Log hours	.0312	.0161	.0183
	(.1477)	(.0942)	(.2598)
	N-4320	N-3511	N-3907

Table A4

Family Covariances (and Correlations) Among the Permanent Components of Log Real Earnings, Log Real Wage Rates, and Log Annual Hours Using Method of Moments Estimators

Mature Women

	Log Earnings	Log Wages	Log Hours
Themselves			
Log earnings	.3761 (1.0000) N-18284	.1753 (.8265) N-17645	.1906 (.8046) N-11893
Log wages	--	.1196 (1.0000) N-27304	.0521 (.3900) N-17564
Log hours	--	--	.1492 (1.0000) N-11593
Sons			
Log earnings	.0863 (.2855) N-15960	.0511 (.2997) N-19466	.0373 (.1959) N-13684
Log wages	.0707 (.3136) N-15070	.0454 (.3572) N-18422	.0216 (.1521) N-12893
Log hours	.0061 (.0608) N-9290	.0034 (.0601) N-11321	.0044 (.0696) N-8003
Daughters			
Log earnings	.1027 (.2730) N-17717	.0617 (.2908) N-21550	.0562 (.2372) N-15093
Log wages	.0543 (.2706) N-18008	.0398 (.3517) N-21953	.0242 (.1914) N-15293
Log hours	.0553 (.2032) N-5877	.0138 (.0899) N-7142	.0408 (.2380) N-5016

(continued)

Table A4--Continued

	Log Earnings	Log Wages	Log Hours
Husbands			
Log earnings	.1142	.0688	.0312
	(.3404)	(.3637)	(.1477)
	N-5313	N-6411	N-4320
Log wages	.0738	.0532	.0161
	(.2720)	(.3477)	(.0942)
	N-4298	N-5227	N-3511
Log hours	.0143	.0115	.0183
	(.1279)	(.1824)	(.2598)
	N-4700	N-5690	N-3907

Table A5
OLS Estimates of Preference, Wage, Hours, and Earnings Equations

Preference Equations (6):

$$U_{ib} = \underset{(.173)}{.096}\, U_{if} + \underset{(.044)}{.030}\, U_{im} + u_{is} + u_{ib}$$

$$U_{ig} = \underset{(.255)}{.634}\, U_{if} + \underset{(.065)}{.277}\, U_{im} + u_{is} + u_{ig}$$

$$\sigma_{u_{ib}} = \underset{(.034)}{.141} \qquad \sigma_{U_{if}} = \underset{(.032)}{.157} \qquad \sigma_{u_{is}} = \underset{(.032)}{.058}$$

$$\sigma_{u_{ig}} = \underset{(.013)}{.434} \qquad \sigma_{U_{im}} = \underset{(.019)}{.356} \qquad \mathrm{Cov}(U_{if}, U_{im}) = \underset{(.006)}{.010}$$

Log Wage Equations (5):

$$W_{ib} = \underset{(.041)}{.299}\, W_{if} + \underset{(.051)}{.253}\, W_{im} + \omega_{is} + \omega_{ib}$$

$$W_{ig} = \underset{(.040)}{.323}\, W_{if} + \underset{(.049)}{.184}\, W_{im} + \underset{(.202)}{.866}\, \omega_{is} + \omega_{ig}$$

$$\sigma_{\omega_{ib}} = \underset{(.017)}{.280} \qquad \sigma_{W_{if}} = \underset{(.012)}{.424} \qquad \sigma_{\omega_{is}} = \underset{(.023)}{.157}$$

$$\sigma_{\omega_{ig}} = \underset{(.018)}{.250} \qquad \sigma_{W_{im}} = \underset{(.013)}{.349} \qquad \mathrm{Cov}(W_{if}, W_{im}) = \underset{(.005)}{.055}$$

Log Hours Equations (2):

$$H_{ib} = \underset{(.050)}{.025}\, W_{ib} + U_{ib}$$

$$H_{ig} = \underset{(.062)}{.167}\, W_{ig} + U_{ig}$$

$$H_{if} = \underset{(.042)}{.026}\, W_{if} + U_{if}$$

$$H_{im} = \underset{(.070)}{.397}\, W_{im} + U_{im}$$

Log Earnings Equations (3):

$$E_{ib} = \underset{(.106)}{1.127}\, W_{ib} + \underset{(.504)}{1.573}\, H_{ib}$$

$$E_{ig} = \underset{(.093)}{.992}\, W_{ig} + \underset{(.055)}{1.063}\, H_{ig}$$

$$E_{if} = \underset{(.081)}{1.161}\, W_{if} + \underset{(.439)}{1.307}\, H_{if}$$

$$E_{im} = \underset{(.123)}{1.061}\, W_{im} + \underset{(.111)}{.971}\, H_{im}$$

Notes:
1. Standard errors are reported in parentheses.
2. The OLS regression producing these results had $R^2 = .99$, RMSE = .0115, Sum of Squared Errors = .0076, and 57 degrees of freedom.

Table A6
WLS Estimates of Preference, Wage, Hours, and Earnings Equations with Restrictions on Wage and Hours Parameters in Earnings Equations

Preference Equations (6):

$$U_{ib} = \underset{(.087)}{.193}\, U_{if} - \underset{(.043)}{.008}\, U_{im} + u_{is} + u_{ib}$$

$$U_{ig} = \underset{(.240)}{-.146}\, U_{if} + \underset{(.098)}{.367}\, U_{im} + u_{is} + u_{ig}$$

$$\sigma_{u_{ib}} = \underset{(.012)}{.144} \qquad \sigma_{U_{if}} = \underset{(.014)}{.175} \qquad \sigma_{u_{is}} = \underset{(.022)}{.068}$$

$$\sigma_{u_{ig}} = \underset{(.016)}{.450} \qquad \sigma_{U_{im}} = \underset{(.016)}{.346} \qquad \mathrm{Cov}(U_{if}, U_{im}) = \underset{(.008)}{.015}$$

Log Wage Equations (5):

$$W_{ib} = \underset{(.039)}{.274}\, W_{if} + \underset{(.047)}{.274}\, W_{im} + \omega_{is} + \omega_{ib}$$

$$W_{ig} = \underset{(.046)}{.264}\, W_{if} + \underset{(.048)}{.215}\, W_{im} + \underset{(.215)}{.813}\, \omega_{is} + \omega_{ig}$$

$$\sigma_{\omega_{ib}} = \underset{(.013)}{.295} \qquad \sigma_{W_{if}} = \underset{(.011)}{.444} \qquad \sigma_{\omega_{is}} = \underset{(.024)}{.164}$$

$$\sigma_{\omega_{ig}} = \underset{(.014)}{.259} \qquad \sigma_{W_{im}} = \underset{(.007)}{.347} \qquad \mathrm{Cov}(W_{if}, W_{im}) = \underset{(.007)}{.057}$$

Log Hours Equations (2):

$$H_{ib} = \underset{(.015)}{.082}\, W_{ib} + U_{ib}$$

$$H_{ig} = \underset{(.047)}{.218}\, W_{ig} + U_{ig}$$

$$H_{if} = \underset{(.027)}{.083}\, W_{if} + U_{if}$$

$$H_{im} = \underset{(.048)}{.445}\, W_{im} + U_{im}$$

Log Earnings Equations (3):

$$E_{ib} = W_{ib} + H_{ib}$$

$$E_{ig} = W_{ig} + H_{ig}$$

$$E_{if} = W_{if} + H_{if}$$

$$E_{im} = W_{im} + H_{im}$$

Notes:
1. Standard errors are reported in parentheses.
2. The WLS regression producing these results had $R^2 = .98$, RMSE = .9512, Sum of Squared Errors = 58.81, and 65 degrees of freedom.
3. The p- value for the SSE drawn from a χ^2_{65} is .69.

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Chapter 3

Effects of Parental Characteristics on the Returns to Education, and Labor Market Experience

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Introduction

This chapter examines whether the education and experience slopes of wages vary systematically with cognitive ability and with family background characteristics that influence the quantity of formal education chosen. This question is of interest for two reasons. First, experience and education are among the two most important determinants of earnings. While there is an enormous literature seeking to measure the relationship between earnings and these two variables, only a few studies have examined the extent to which the return to these variables depends on worker characteristics. In particular, little is known about how family background influences the wage benefits of education and of time spent in the labor market. This is surprising in light of the fact that there is an extensive literature documenting the effects of parental characteristics on both the educational attainment and on the income of children. The literature on parental effects on children's income focusses on the direct effect of inherited ability and family environment on wage levels rather than on the effects of these variables on the rate of return to

education and experience.[1] Some educational attainment studies have examined the influence of parents' education and financial resources on years of schooling and achievement in school, and a smaller number have examined parental effects on school quality.[2] However, there is little evidence on whether parents and the family influence the rate of return to education and experience in the labor market.[3] More generally, little is known about the determinants of the value of a year of school.[4]

Our second reason for being interested in family determinants of education slopes is as a source of family differences in the demand for

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1. For example, all of the studies surveyed in Griliches (1979) assume that the rate of return to education is the same for all individuals.

2. See Siebert (1985) for a discussion of this literature and detailed references.

3. We discuss a parallel study by Altonji (1988) below. Hauser (1973) finds little evidence that father's occupation has much effect on the return to education for men in a cross section analysis that permits the education slope and intercept to vary with father's occupation. Using the Kalamazoo twins data, Olneck (Chapter 6 in Jencks et al., Who Gets Ahead?) finds little evidence that education slopes differ by IQ or by father's education.

4. Altonji (1988) and Morgan and Sirageldin (1968) are examples of studies that examine the relationship between school variables and future earnings and provide references to a small number of other studies. There is a large literature on race and sex differences in the rates of return to education. (See Cain (1986) and Welch (1973).) However, Welch (1973) and a recent paper by Card and Krueger (1990) are among a handful of studies that have looked at the effects of schooling inputs on the returns to education. Card and Krueger find substantial effects of student/teacher ratio, the relative salary of teachers, and the length of the school term on estimates of the rates of return to education. They rely on variation across states and age cohorts in these input measures and do not control for differences in parental inputs. To the extent that differences in the average education of parents raises the demand for school quality in a state and has a positive direct effect on rates of return to education, their results may overstate the effects of school inputs on the return to education. On the other hand, we find little evidence below of a substantial effect of parental education on the return to education.

education. In our data set the correlations of education levels between matched family members are .46 for fathers and sons, .43 for mothers and sons, .40 for fathers and daughters, .41 for mothers and daughters, .58 for brothers, .50 for sisters, and .48 for brothers and sisters. Most studies of educational attainment take the view that family background affects education primarily by influencing the amount of education individuals obtain, holding the rate of return to education constant. However, education choice models such as Willis and Rosen (1979) imply that family background characteristics that raise the rate of return to schooling may induce individuals to stay in school longer. Perhaps the strong parental and sibling correlations in years of education arises in part because there is a correlation across family members in the economic value of education.

In this chapter we take advantage of the NLS data on sibling pairs to estimate a simple model which measures parental effects on the education and experience slopes of children. Consider a standard wage equation in which the log wage is specified to depend upon education, and experience, and a set of control variables. We allow the education and experience coefficients to depend upon on other variables, including father's education and mother's education, and an index of family background variables, school characteristics, and personal characteristics that predict years of education completed. We also examine the interaction of the effect of IQ on the relationship between years of education and the wage. Since education as well as the interaction between education and parent's education are likely to depend upon unobserved family characteristics that have an independent influence on wages, there is a strong possibility that omitted family variables will bias estimates of the return to education. We deal with this

by using a sibling fixed effect to control for unobserved variables that are common to siblings. Of course, controlling for the family does not eliminate idiosyncratic differences among siblings in cognitive ability and motivational factors which have an independent effect on both wages and education. In most of our specifications, we control for a measure of IQ to reduce the possibility that ability differences between siblings will lead to biases in the estimated returns.[5] Our hope is that most of the remaining bias is absorbed by the estimate of the main effect of education on wages rather than by the estimates of the extent to which background variables shift the estimates of education. Below we analyze the potential biases using a simple model of wages and the demand for education.

Our main result is that the effect of the child's IQ, father's education, mother's education, and index of family background, secondary school characteristics, and personal characteristics that predict years of schooling completed have only weak influences on the relationship between education and wages, and between labor market experience and wages. In a number of cases, the family background interactions work in the wrong direction or are statistically insignificant. In view of the results, it seems unlikely to us that the effect of family background on the education slope of wages is responsible for more than a small part of the powerful effect of family background on years of school completed.

The paper is organized as follows. Section I presents the econometric framework for the study. Data issues are addressed in section II. Section III presents the empirical results, and in section IV we summarize the

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5. The basic approach was implemented in Altonji (1988) using a small sample for the Panel Study of Income Dynamics, without a control for IQ. His results are discussed below.

findings and offer some suggestions for future research.

I. Econometric Framework

Consider the following log wage equation for a young woman:

$$(1)\quad W_{dht} = Z_{dht}B_1 + Z_{mh}B_2 + Z_{fh}B_3 + r_{dh}ED_{dh} + \Gamma_{dh}EXP_{dht} + \epsilon_d + \epsilon_h + u_{dht}$$

In (1) W_{dht} is the log wage, and Z_{mh} and Z_{fh} are characteristics of the mother and father, respectively. The variable ED_{dht} is education, and EXP_{dht} is labor market experience. The vector Z_{dht} consists of other observed characteristics of the woman that affect her wage rates. For expository convenience, we work with a linear specification of the education and experience profiles. However, in most of our empirical work we include an interaction term between education and experience, a cubic specification in education, and a quadratic in experience. Finally, ϵ_d and ϵ_h are individual specific and family specific error components; u_{dht} is a transitory error component that we assume is uncorrelated with the other right hand side variables in the equation.

The education and experience slopes r_{dh} and Γ_{dh} depend on family background characteristics that are related to innate cognitive ability, quality of early childhood development, primary and secondary school quality, the amount of time and energy that children devote to schooling when in primary and secondary school, and the success of parents as aides in the formal schooling process and as informal teachers at home. Specifically,

$$(2)\quad r_{dh} = a_1 X_{fh} + a_2 X_{mh} + r + v_h$$

$$\Gamma_{dh} = b_1 X_{fh} + b_2 X_{mh} + \Gamma + \mu_h$$

where v_h and μ_h are unobserved household specific error components affecting rates of return to education and experience. The variables v_h and μ_h may be correlated. One can easily generalize (2) to include person specific variables such as IQ scores, and we do so in the empirical work below.

Using (2) to substitute for r_{dh} and Γ_{dh} in (1) leads to

$$\begin{aligned}(3)\quad W_{dht} &= Z_{dht}B_1 + Z_{mh}B_2 + Z_{fh}B_3 \\ &+ [r + a_1 X_{fh} + a_2 X_{mh}]ED_{dh} + [\Gamma + b_1 X_{fh} + b_2 X_{mh}]EXP_{dht} \\ &+ \epsilon_d + \epsilon_h + v_h ED_{dh} + \mu_h EXP_{dht} + u_{dht}\end{aligned}$$

Because ED_{dh} is likely to be correlated with the error terms ϵ_h and v_h, least squares estimation of the above equation will lead to biased parameter estimates. However, by differencing (3) for pairs of siblings one can eliminate the terms involving ϵ_h from the equation. For siblings indexed by d and d', the differenced equation is

$$\begin{aligned}(4)\quad W_{dht} - W_{d'ht} &= [Z_{dht} - Z_{d'ht}]B_1 \\ &+ [r + a_1 X_{fh} + a_2 X_{mh}]\,[ED_{dh} - ED_{d'h}] \\ &+ [\Gamma + b_1 X_{fh} + b_2 X_{mh}][EXP_{dht} - EXP_{d'ht}] \\ &+ \epsilon_d - \epsilon_{d'} + v_h[ED_{dh} - ED_{d'h}] + \mu_h[EXP_{dht} - EXP_{d'ht}] + u_{dht} - u_{d'ht}\end{aligned}$$

The error components v_h and μ_h are constant within the household and so

will be uncorrelated with the explanatory variables in the above equation.

However, potential simultaneity problems could arise from the term $\epsilon_d - \epsilon_{d'}$, if these idiosyncratic components capturing differences in productivity, say, are correlated to the differences in the education levels chosen by siblings d and d'. In a number of the specifications below, we try to mitigate this problem by adding a measure of IQ to (3), which implies that the difference between the IQ scores of d and d' will appear in (4). However, IQ is almost certainly not a perfect control, and in the next few paragraph we use a simplified model of wages and the demand for education to examine whether our estimates of the effects of parental education on returns to education will be subject to bias.

Suppose that a_2 in equation (2) is equal to zero, that there is no experience slope, and theat Z_{dht} is a constant for all siblings. Also, without much loss of generality, suppose we ignore the transitory wage components. Then (4) reduces to

$$(5)\quad W_{dh} - W_{d'h} = [r + a_1 X_{fh}]\,[ED_{dh} - ED_{d'h}] + \epsilon_d - \epsilon_{d'} + v_h[ED_{dh} - ED_{d'h}]$$

Let the young woman's demand for education be

$$(6)\quad ED_{dh} = C_1 + C_2 X_{fh} + C_3 \epsilon_d + C_4 v_h + \omega_d$$

where C_1 is a constant, $C_2 > 0$, $C_3 > 0$, and $C_4 > 0$. One can easily derive (6) from a model in which individuals seek to maximize the present discounted value of lifetime income, and where the education slope in the wage equation

is related to X_{fh}, ϵ_d, v_h, and ω_d, and the interest rate used to discount future income depends upon one or more of these variables and on the number of years of education chosen.

Finally, assume that X_{fh} takes on only two values, 0 and 1. Suppose one estimates (5) separately for families with $X_{fh}=0$ and $X_{fh}=1$. The probability limit of the estimator of r for the $X_{fh}=0$ sample will be

$$(7)\quad r + \frac{\mathrm{Cov}([ED_{dh} - ED_{d'h}],\ \epsilon_d - \epsilon_{d'} + v_h[ED_{dh} - ED_{d'h}] \mid X_{fh}=0)}{\mathrm{Var}(C_3\ [\epsilon_d - \epsilon_{d'}] + [\omega_d - \omega_{d'}] \mid X_{fh}=0)}$$

The probability limit of the estimator of $r + a_1$ for the $X_{fh}=1$ sample is

$$(8)\quad r + a_1 + \frac{\mathrm{Cov}([ED_{dh} - ED_{d'h}],\ \epsilon_d - \epsilon_{d'} + v_h[ED_{dh} - ED_{d'h}] \mid X_{fh}=1)}{\mathrm{Var}(C_3\ [\epsilon_d - \epsilon_{d'}] + [\omega_d - \omega_{d'}] \mid X_{fh}=1)}$$

The difference between (8) and (7) is the probability limit of the OLS estimator of a_1 that one would obtain if one used the pooled sample of families to estimate (5).

It follows that if the conditional variances and covariances in the above expressions are independent of X_{fh}, then the difference in the coefficients from the two separate regressions is a consistent estimator of a_1 even though (7) is an inconsistent estimator of r and (8) is an inconsistent estimator of $r + a_1$. The argument can easily be generalized to the case in which X_{fh} takes on a variety of values.

In practice, our specifications include nonlinear education terms and

other explanatory variables. Some specifications include more than one interaction term with education, and all of our models include a measure of experience, which was omitted from the above discussion entirely. But the above analysis provides some basis for believing that the bias in the estimate of a_1 (the influence of the father's characteristics on the daughter's return to education) will be small even if the bias in the estimate of r is large.

A Fixed Effect Approach

In practice, it is not efficient to work with the differenced equation (4). Our panel data set provides more than one observation on (3) for most individuals in the sample. Furthermore, for some households more than one sibling is in the sample, and for others only one child is in the sample. In these circumstances a more efficient estimation approach is to work with (3) and include a separate intercept for each family (a fixed effect) to eliminate c_h. This permits us to use the time variation in experience for each individual to identify experience effects and the effects of parental characteristics on the experience slope even in the case of individuals who do not have a sibling in the sample. It is also a convenient way to use all of the data on households with more than two children. Applying OLS to (3) with a separate constant for each household is equivalent to estimating

$$
\begin{aligned}
(9)\quad W_{dht} - W_h = {} & (Z_{dht} - Z_h)B_1 + \\
& + [r + a_1 X_{fh} + a_2 X_{mh}](ED_{dh} - ED_h) + v_h(ED_{dh} - ED_h) \\
& + [\Gamma + b_1 X_{fh} + b_2 X_{mh}](EXP_{dht} - EXP_h) + \mu_h(EXP_{dht} - EXP_h) \\
& + c_d - \bar{c}_d + u_{dht} - u_h
\end{aligned}
$$

where Z_h are the averages of the characteristics of all the daughters in household h, ED_h is the average education level and EXP_h the average labor market experience of the daughters in household h, $\bar{\epsilon}_d$ is the average daughter component, and u_h is the average idiosyncratic component of their wages.

When data for only one daughter from household h is available, the terms involving $(ED_{dh} - ED_h)$ drop out of (9), but the experience terms, including the interaction, remain.

We use the same framework to study young men and brothers. When we pool data for young men and young women we permit all of the coefficients involving experience and education, except the interactions between X_{fh} and X_{mh} to vary with gender. We also allow for separate intercepts for males and females. In pooled case we are implicitly assuming that unobserved common family characteristics have the same effect on both young men and young women. If the effects enter differently for males and females, then they will not be eliminated when we add a separate intercept for females to (9).[6] Consequently, we are not sure how much emphasis to place on the fixed effects results based on the pooled sample.

3. Data

The data are based on the Young Men and Young Women cohorts of the NLS. The sample selection criteria and most of the variables are discussed in Chapter 1. The dependent variable in all regressions is the log of the young man's or woman's reported wage for a given year. Note that an individual may

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[6]. In Chapter 2 we find that there do exist gender differences in the effects of parental wage factors and of "sibling" wage factors on the wage rates of young men and young women.

contribute more than one observation to his or her sample.[7] The measures of parental education (DADED and MOMED) are based on young men and young women's survey reports, since the use of information provided by the parents themselves would limit the sample to only those young men and young women whose parents are found in the mature women and older men's cohorts. Missing data on IQ scores and on mother's and father's education poses a problem for the study. When IQ is missing, (31 percent of the sample for young men and 30.5 percent for young women) we code all variables that depend on IQ as zero. All of our equations that involve IQ also include a dummy variable that is one if data on the IQ score are missing and is zero otherwise. Missing data for DADED (25.1 percent for young men, and 26.9 for women) and MOMED (13.3 percent for young men, and 10.9 for women) are handled in the same way. Since missing data on DADED are likely to be related to whether the individual's father was present in the household while he or she was growing up, we feel that it is inappropriate to simply eliminate cases with missing data from the analysis.[8]

In addition to IQ, DADED, and MOMED, we constructed a predicted educational attainment variable called EDINDEX. EDINDEX is a measure of the deviation of a child's "expected" highest grade completed from his or her group's mean expected highest grade completed. It was constructed as the predicted value from a regression of the child's highest grade completed on a set of parental and school quality variables that predict education, and perhaps influence the child's potential wages. Specifically, the parental

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7. In fact, the average number of observations per young man is 4.66; 3.66 for young women. See this chapter's Appendix for summary statistics and more detailed descriptions of the young men's and women's data sets.

8. As we note below, most of our results are robust to restricting the sample to individuals with nonmissing data on IQ, DADED, MOMED, and EDINDEX.

variables are race, parents' educational goal for child at age 14, parental encouragement to continue education past high school, and indicators for whether the natural father was present and for whether the natural mother was present in the household when child was 14 years old, for whether the mother worked when child was 14 years old (young men were not asked this question), and for whether there were two parents (including step- parents) in the household when the child was 14 years old. The school quality measures are a normalized school quality index, student-teacher ratio, counsellor-student ratio, mean teacher's salary, expenditure/pupil, average hours of homework/pupil, and indicators for private school, child's subjects most liked and disliked, and curriculum type (college preparatory, commercial, or vocational). We re-code variables that are missing for a particular individual to zero and include missing variable indicators in the equation. The regression equation used to compute EDINDEX was estimated separately for young men and for young women. For each group EDINDEX is normalized to have a mean of zero.

The hypothesis underlying our use of EDINDEX is that variables that influence how much education individuals obtain also influence the response of wages to a year of schooling. There are too many variables that could be related to the quality of schooling to investigate each separately.

We work with cubic specifications for education and IQ and a quadratic for experience. We parameterize the models so that the coefficient on the linear education term is the marginal rate of return to education for an individual with 12 years of education. When interactions between education and any or all of IQ, DADED, MOMED, and EDINDEX are included, the equations are parameterized so that the coefficient on education is the marginal rate of

return to education for an individual with 12 years of education, an IQ of 100, the sample mean of EDINDEX (which is zero), and a mother and father who each have 12 years of education.[9]

Although not shown in the tables, all equations without family fixed effects include dummy variables for the year for which the wage is reported, child's race, residence in an SMSA, residence in the South, two parents in the household when the child was age 14, in addition to number of siblings, experience (more precisely, potential experience, calculated as number of years since last enrolled in school)[10] and experience squared, and the child's education interacted with his or her experience.[11] In the models with family

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9. All specifications that include interactions between education and any or all of IQ, DADED, MOMED, or EDINDEX also include interactions between education and the corresponding missing dummy variable(s).

10. In creating the experience variable we set experience to (age - 14) for those who never enrolled in school or had zero years of schooling. We set it to age minus the school leaving age for other cases. Unfortunately, we did not notice until after the paper was essentially completed that the school leaving age is inconsistent with the data on age and/or the years of schooling in a few cases. As a result, (age - experience) is less than 14 years for 1.0 percent of the young men's observations and 2.6 percent of the young women's observations. This explains the fact that the difference in Table A1 between the maximum of age and the maximum of experience is 11 years for men and 8 years for women.

When we eliminate these observations and re-estimate the young men's wage equation with fixed effects (Table 5, column 1), the effect of the first year of experience for an individual with 12 years of education falls from 2.65 to 2.59. The effect of education for an individual with 12 years falls from 3.27 to 3.08. For young women the effect of the first year of experience falls from .634 to .544 and effect of education falls from 7.48 to 7.19 (Table 7, column 1). We re-estimated all of the models reported in the tables and found that in all cases the interactions of father's education, mother's education, EDINDEX, and IQ with education and with experience are not dramatically different from those reported in the tables.

11. In the models <u>with</u> family fixed effects, race and number of siblings are excluded from the control variables since they should be constant within the family, and therefore their effects are captured by the family fixed effect. For consistency when we work with the young men's data set, we replace each young man's reports of DADED and MOMED in the interaction terms with the average of the reports of all the brothers in the family. Similar

fixed effects, those individuals who do not have siblings in the sample help to identify the effects of experience, the year, and the residence variables.

III. Estimation Results

In section III.1 we discuss the effects of father's education and mother's education on the education slope. In sections III.2 and III.3 we consider the effects on the education slope of IQ and of the index of determinants of education. In section III.4 we discuss the effects of the various interaction terms on the experience slopes of young men and young women.

III.1 The Effects of Father's and Mother's Education on the Education Slope

Table 1 presents a set of wage equations for young men with a fixed effect included for each family. All coefficients and standard errors have been multiplied by 100 to make the tables easier to read.[12] To provide a basis for assessing whether family background has an important influence on education slopes, we first discuss the size of the effect of education on wages for a typical individual with 12 years of education. A base line

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recodings are done for the young women's data set, and the pooled data set when family fixed effects were added. Nearly 96 % of young men who have brothers supply a DADED report that differs by no more than one half year from the average report over all the brothers in the family. For mother's education, the figure is 94%. For young women, the corresponding percentages are 93, and 93. Finally, for the pooled sample of young men and young women, 83% of individuals have a DADED report within one half year of the average over all his or her siblings' reports, 85 % for MOMED.

12. Standard errors have not been corrected to account for the serial correlation across time for a given individual. The standard errors for the equations without fixed effects also ignore correlation among the errors terms of members of the same family.

equation with all background interaction effects excluded is reported in column 1 of the table. The coefficient on education is to be interpreted as the marginal effect of education when education equals 12 years. The estimated coefficient is 3.41 with a standard error of .801.[13] When we add a cubic specification for IQ, the education coefficient falls to 3.27 (column 2).

In column 4 we add the interaction between father's education and the son's education. The coefficient is .039, which has the expected sign, but is small in magnitude relative to the main effect of an additional year of education, and is not significantly different from zero. The interaction between mother's education and the son's education in column 5 has a coefficient (standard error) of .286 (.199). This result is consistent with a modest effect of mother's education on the return to education, but the evidence is weak. However, when we restrict the sample to individuals with nonmissing data on all of DADED, MOMED, IQ, and EDINDEX, the coefficient on the mother's education interaction rises to .730 and is significant. When we allow for both parents' interactions (in column 6 of Table 1) the coefficient on the mother's education interaction increases and the father's becomes negative. Both coefficients are imprecisely estimated, though.

In an effort to get more precise estimates at the cost of possible bias from the omitted family variables that are correlated with the young man's education and his parents' education, we report estimates <u>without</u> family fixed

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13. When fixed effects are included, we estimate the difference in log wages (times 100) associated with increasing education from 10 years to 12, 14, and 16 to be 6.33, 14.10, and 23.25 (respectively). For young women the corresponding estimates are 15.47, 30.18, and 41.87. When fixed effects are excluded, the estimates are 8.82, 18.06, and 27.14 for young men and 11.74, 24.87, and 38.90 for young women.

effects in Table 2. The estimate of the rate of return when only parents' education is controlled for (column 1) is 4.39, which is in the low range of estimates from other studies that do not contain detailed controls for family variables. (Recall that when family fixed effects were controlled for, the education coefficient was 3.41). The interaction between father's education and the son's education has a coefficient of .074 with a standard error .034. The interaction between mother's education and son's education has a coefficient of .080 with a standard error of .036. When we include both parents' interactions, both coefficients fall somewhat.

Taken together, the results with and without family effects imply that parental education has a small positive effect on the relationship between education and wages for young men. A point estimate of .1 implies that 4 additional years of parent education raises the child's rate of return by .4, which is modest relative to an overall return to education of 4 or 5 percent.

Results for Women

Tables 3 and 4 report wage equations for young women that are comparable to Tables 1 and 2 for young men. Table 3 includes fixed effects for each family, while Table 4 does not. The base line specifications in column 1 of each of the two tables indicates that the rate of return to education is higher for young women than for young men, and actually increases from 6.26 to 7.78 when we control for family effects (recall that for young men, the education coefficients are generally lower when we include family fixed effects). Altonji (1988) reports a similar pattern using matched data on sisters from the Panel Study of Income Dynamics. The education slopes with and without fixed effects seem to indicate that unobserved family variables

that raise wages for young women are associated with fewer years of education, while the opposite is true for young men. The asymmetry is surprising and deserves careful investigation in future work. Associated with it is a peculiar pattern in which the effect of IQ (level) actually changes from positive to negative when we control for family effects (compare columns 2 through 7 of Tables 3 and 4). When fixed effects are excluded, the coefficient on IQ is similar for young men and young women, around 0.30.[14]

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[14]. For young men, the main effect of IQ has a positive and statistically significant effect on the log wage in nearly all specifications. When family fixed effects are included, the coefficients on the linear, quadratic, and cubic terms imply that the wages of individual in the 75th percentile of IQ scores are 5.6 % higher than individuals in the 25th percentile. When family fixed effects are excluded, the corresponding differential is 5.5 %. For young women we obtain a differential of 5.2 % when family fixed effects are excluded. However, when we add family fixed effects we obtain a negative IQ differential equal to 5.9 %.

We do no have a full explanation for this puzzling result, although it appears to be due in part to an anomaly in the sample of young women who have sisters. We re-estimated our equations without fixed effects on the sample of young women who have sisters in the sample, since this is the sample that identifies the effect of IQ once family fixed effects are added to the equation. In the basic specification in column 2, the effect of IQ is .15 (not significantly different from zero), which is well below value of .30 for the full sample. (In models with family fixed effects, the coefficient estimates are about equal in the two samples.)

We also reestimated the model on a sample that excludes those young women for whom IQ is missing and obtained a negative but statistically insignificant coefficient when fixed effects are included. Years of schooling, wage rates, and EDINDEX are systematically lower for young women for whom IQ is missing. However, the same pattern holds for young men as well. (Since the IQ score was provided by the respondent's high school, it is not surprising that it is more likely to be missing for those who have fewer years of education.) The correlation between IQ and highest grade completed, the time average of the log wage rate, the time average of log hours worked per week (for those who worked positive hours), and EDINDEX are .50, .27, .05, and .48 respectively in the case of young men and .44, .31, -.04, and .46 in the case of young women. Thus, the gender differences in the raw correlations are small.

We also investigated the possibility that part of the return to IQ for young women comes through an effect on the earnings of potential spouses. When we substituted family income for the log wage rate as the dependent variable in the model, we obtained positive IQ coefficients (multiplied by 100) between .01 and .31 when fixed effects are included and a positive coefficient of about .400 without fixed effects.

The coefficient on the interaction of daughter's and father's education (in column 4 of Table 3) implies that a year of father's education past high school increases the daughter's education slope by .116 with a standard error of .187. The corresponding interaction term with mother's education has a coefficient of .547 with a standard error of .212.[15] These results imply a substantially more powerful effect of parental education (especially the mother's) on the education slope for young women than for young men. (Recall, for young men the corresponding estimates were .039 and .286.) In column 6 we again see the mother's education effect becomes stronger and the father's weaker when they enter together in the equation with family fixed effects.

However, both of the parents' education interaction terms become small and negative when family fixed effects are dropped from the analysis; see columns 4 and 5 in Table 4. Although we prefer the estimates with fixed effects included, the imprecision of the estimates in that case preclude us from drawing strong conclusions about the effects of parental education on the education slopes for women. It is also worth noting that Altonji (1988) obtains quantitatively important effects of parental education on the education slopes for young men, but does not find much of an effect for young women. In view of these mixed results, we conclude is that we do not have much evidence that parental education has a strong effect on the return to education for either young men or young women.

III.2 The Effects of IQ on the Education Slope

A number of the specifications include an interaction of the child's

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15. This estimate rises to .820 when the sample is restricted to individuals with nonmissing data on IQ, DADED, MOMED, and EDINDEX.

education with his or her IQ. We are surprised to find that the interaction term is typically negative (and insignificant) with a coefficient of -.015 to .010 for young men. For young women, the IQ interaction coefficient is between .000 and -.057 (and insignificant) when fixed effects are included. When we add fixed effects, the coefficient is -.085 and is highly significant. Thus, we have little evidence that those with higher IQ's benefit more (in percentage terms) from additional years of schooling.

III.3 The Effects of EDINDEX on the Education Slope

Column 7 of Table 1 adds the interaction of education and EDINDEX and the level of EDINDEX to the equation containing cubic specifications of education and IQ, a family fixed effect, and the other standard controls for young men. The main effect of EDINDEX is large and positive (2.81) with a standard error of .734, but the interaction term is negative and insignificant.[16] When the family fixed effects are excluded (Table 2), the coefficient on the education-EDINDEX interaction is .083, but it is not significantly different from zero. (Without fiexed effects, the coefficient on EDINDEX falls from 2.81 to 1.23 with a standard error of .239).[17]

For young women, we obtain EDINDEX interaction coefficient estimates (standard errors) of .086 (.103) when family effects are excluded (Table 4,

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16. Omitting the education-EDINDEX interaction did not have much effect on the coefficients on EDINDEX reported in column 7 of the various tables.

17. Measurement error in reported education might be partially responsible for the positive coefficient on EDINDEX. The decline in the EDINDEX coefficient would be expected if the proportion of the variance in EDINDEX that is across families exceeds the corresponding proportion for education. It might be possible to improve upon our estimates by using the education reports provided by relatives (e.g., parents, brothers or sisters) as instruments for the education reports provided by the respondents.

column 7) and .310 (.310) when family effects are included (Table 3, column 7). The latter indicates that a 3 year difference in predicted education is associated with a difference of almost 1 percentage point in the young woman's rate of return to education. However, the coefficient has a standard error of .310, and is therefore not precisely estimated.

In column 8 of Tables 1 and 2 we simultaneously include the interactions of education with IQ, DADED, MOMED, and EDINDEX in the wage equations for young men. When fixed effects are included (Table 1) the parents' education, IQ, and EDINDEX interactions are all insignificant. When fixed effects are excluded (Table 2) the EDINDEX interaction coefficient increases to .240 with a standard error of .087, while the parents' terms and the IQ interaction remain insignificant. The same general pattern of coefficient changes is observed in the young women's models in Tables 3 and 4.

In summary, we do not have strong evidence that variables that are related to the number of years of education completed have much of an effect on the education slope of wages, although the education-EDINDEX interactions are typically positive and significant in the models that exclude fixed effects and include all of the interaction terms. The level of EDINDEX was found to have a strong positive effect on wages, particularly in the models including fixed effects.

It is also interesting to note that adding EDINDEX reduces the main effect of education. For example, for young men when fixed effects are excluded the education coefficient falls from 3.78 to 3.27 when EDINDEX is added as a control variable (Table 2, columns 2 and 7). The drop is even more dramatic in the models with family fixed effects: from 3.27 to 2.16 (see Table 1). Evidently, variables that are positively related to educational

attainment, and are captured by EDINDEX, have a positive direct effect on wages. This is consistent with evidence that the education slope is biased upward by omitted variables that are correlated with education.[18] However, an alternative explanation is that measurement error in education, which would tend to lower its coefficient, has more of an influence on the education slope once EDINDEX is controlled for. (See footnote 17 for a further discussion.)

III.4 The Effects of IQ and Parental Education on Experience Slopes

Table 5 reports estimates of the interactions between <u>experience</u> and education, IQ, father's education, and mother's education for young men with family fixed effects included in the equations.[19] In column 1, the effect of

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18. Screening models emphasize that education has value in the market because it reveals information about worker quality that is difficult for employers to observe directly. Consequently, to the extent that the variables that are included in EDINDEX are hard for employers to observe directly and are indicators of productivity, the decline in the education coefficient is consistent with signalling models that imply that the return to education is in part a return to worker characteristics that are correlated with-- but are not changed by-- secondary and higher education.

However, to the extent that the variables comprising EDINDEX are easily observable, screening models would seem to predict no decrease in the coefficient on education when EDINDEX is added as a regressor. It may be possible to base a test of the screening model on the relative effects on wages of the component of education that can be predicted from information that employers observe and of the component of education that is unpredictable. Clearly, the problem in implementing such a test is uncertainty about what information employers actually can observe.

19. In all equations that we report, we include an interaction between education and experience. (The size of the coefficients and associated standard errors of the other interaction terms are only slightly sensitive to the omission or addition of the education-experience interaction term.) The coefficient on this variable is positive, large, and significant for young men-- around .120 with a standard deviation of .030-- indicating that 4 more years of education raises the linear term in the experience slope by .36 to .51, which is large given that the linear term in the experience slope for an individual with 12 years of education is 3.27 when family fixed effects are included. However, we do not find these effects for young women: though the estimated coefficients are all negative, none are significant (see Tables 7 and 8).

one additional year of experience for an individual with no previous experience, 12 years of education, a father and mother each with 12 years of education, and an IQ of 100 is 2.61. The interaction between IQ and experience in column 2 has a coefficient (standard error) of .017 (.005), implying that a 20 point increase in IQ raises the experience slope by .34.[20]

Father's education has a small negative and statistically insignificant interaction with experience and is not very sensitive to whether one controls for the interactions between experience and mother's education and between experience and IQ (see columns 3, 5 and 6). The mother's interaction term is also small, negative, and insignificant in the models with family fixed effects (see columns 4, 5 and 6).

When we do not control for family fixed effects (Table 6) the IQ interaction coefficient rises to .029 with a standard error of .005, and the father's education interaction term rises to .028 with a standard error of .019. However, the coefficient on the interaction between experience and mother's education remains negative and insignificant.

Tables 7 and 8 report a parallel set of results for young women. The coefficients on the IQ-experience interaction are small in magnitude and statistically insignificant whether or not family fixed effects are included. Similarly, the father's and mother's education interaction terms are statistically insignificant and small in magnitude.

In summary, we do not find a strong positive effect of parental education on the experience slopes. In most cases, the point estimates are small, and in some cases, negative. Evidently, the relationship between parental

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20. In our sample of young men the 25th and 75th percentiles of the IQ measure are 92 and 112 while the mean is 101.6 and the standard deviation is 15.9. For young women, the corresponding figures are 93, 112, 102.2 and 15.2.

education and general human capital obtained prior to entering the labor market is not strong enough, given the strength of the link between general human capital and investment in on-the-job training, to influence the experience slope. It is interesting to note that IQ has only a small effect on the experience slope. Also, while the experience slope is steeper for more highly educated men, it is (if anything) slightly flatter for more highly educated women.[21] Consequently, the weak relationship between parental education and experience slopes is consistent with the lack of a strong, consistent relationship between the child's own education and ability and his or her experience slope.

IV. Discussion and Conclusion

It should be kept in mind that these results do not rule out the possibility that family characteristics, school characteristics, and individual characteristics that affect expected schooling alter the ex ante return to education. When the effect of education on wages is nonlinear, the

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21. When we pool the young men's and young women's samples and add family fixed effects we find that the experience slope is more than 3 points lower for females than males. It should be kept in mind that our experience measure is a measure of potential experience subsequent to completion of schooling, which may partially explain the smaller coefficient for females.

We also find that coefficients on the interaction between education and experience is typically .085, suggesting a substantial effect of education on the experience slope. This qualitative result and the empirical magnitude is consistent with most of the evidence of which we are aware.

The IQ-experience interaction has a coefficient of .013 (with a standard error of .004) when we use the pooled sample and include family effects, indicating that a 10 point increase in IQ will raise the experience slope by between .05 and .08. The estimate is .021 with a standard error of .004 when family effects are excluded.

Finally, the coefficients on the experience-father's education, and experience-mother's education interactions, which are a main focus of our analysis, are small in magnitude and never statistically significant when we pool the young men's and young women's data.

ex ante return must take account of the fact that educational outcomes are uncertain. Variables that affect years of schooling may raise the ex ante return even if they have no effect or a small negative effect on the response of wages to a given number of years of schooling. To see this, note that if most of the return to college is associated with graduation, then variables that lower the value of a college degree but increase the probability of graduation conditional on starting college may raise the ex ante rate of return to starting college.[22]

A simple way to investigate these issues is to estimate wage equations which do not include education squared and cubed as regressors. In this case, the interaction terms should "get credit" for differences in the average return to education associated with different education levels. Tables 9 and 10 report the results of wage regressions which included linear specifications of education. The results are basically similar to the estimates discussed above.[23]

In this paper we have explored the possibility that education and experience slopes of wage equations are influenced by IQ, parental education, and an index of family background variables, school characteristics, and personal characteristics that predict years of education completed. Our main result is that the effect of the child's IQ, father's education, mother's

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[22] See Weisbrod (1962) for the initial discussion of this distinction and Altonji (1989) for an empirical analysis of ex ante rates of return using data from the High School Class of 1972. He finds that favorable family background and individual characteristics raise the ex ante rate of return to starting college even though his methodology assumes that wage response to education is the same for all individuals.

[23] These results are only suggestive, since variables that have only small effects on average returns may have large effects on marginal returns. To address these issues, it would be necessary to adopt the methodology of Altonji (1989), which is beyond the scope of this paper.

education, and index of family background, secondary school characteristics, and personal characteristics that predict years of schooling completed have only weak influences on the relationship between education and wages, and between labor market experience and wages. In a number of cases, the family background interactions work in the wrong direction or are statistically insignificant. In view of the results, it seems unlikely to us that the effect of family background on the education slope of wages is responsible for more than a small part of the powerful affect of family background on years of school completed.

A substantial research agenda remains. First, we wish to emphasize that in a number of cases, particularly when family fixed effects are included, our estimates are imprecise. Furthermore, the findings for young men are at variance with results in Altonji (1988) using a sample of young men from the PSID. We plan to replicate our analysis using the most recent data from the PSID, which contains large samples of siblings. The recent results of Card and Krueger suggest that educational inputs can have large effects on education slopes. On the other hand, the literature of schooling achievement suggests that family background and peer characteristics are the most important variables in measured educational achievement. There is strong evidence that parental characteristics in particular have a strong relationship to the level of earnings and to the number of years of schooling. It remains to be the seen whether they have a substantial effect on education and experience slopes in wage equations.

Table 1

The Effects of IQ and Parental Education
on Wage Levels and Education Slopes

Dependent Variable: Log Real Hourly Wage (1967 Dollars)

Explanatory Variables	Young Men							
	Equations with Family Fixed Effects[1] (Coefficients and Standard Errors Have Been Multiplied by 100)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education[2] (based on a cubic specification)	3.41 (.801)	3.27 (.834)	2.27 (.990)	2.69 (1.08)	4.63 (1.03)	3.86 (1.12)	2.16 (.889)	1.84 (1.26)
Education × Experience	.117 (.028)	.117 (.028)	.117 (.028)	.118 (.028)	.119 (.028)	.120 (.028)	.117 (.028)	.121 (.028)
Education × IQ	--	--	.000 (.040)	--	--	--	--	.010 (.040)
Education × DADED[2]	--	--	--	.039 (.164)	--	-.180 (.187)	--	-.216 (.189)
Education × MOMED[2]	--	--	--	--	.286 (.199)	.438 (.229)	--	.406 (.232)
Education × EDINDEX	--	--	--	--	--	--	-.367 (.238)	-.355 (.265)
IQ[3] (based on a cubic specification)	--	.269 (.115)	.315 (.132)	.277 (.115)	.216 (.116)	.226 (.116)	.255 (.116)	.226 (.133)
EDINDEX[4]	--	--	--	--	--	--	2.81 (.734)	2.75 (.754)

NOTES:

1. In addition to the variables reported, all regressions contain the following control variables: year dummies, experience (defined as the number of years since last enrolled in school), experience squared, and indicators for residence in an SMSA and in the South, two parents in the household when the child was 14 years old, and indicators representing missing variable reports.

2. Education is defined as highest grade completed minus 12, so its coefficient is read as the additional wage accruing to a year of education past high school. DADED is the average report over all brothers in the family, rather than the individual young man's report, of father's education minus 12; mother's education (MOMED) is constructed similarly.

3. IQ is defined as the individual's reported IQ score minus 100.

4. EDINDEX is an index of parental influence and school quality factors which predict number of years of education.

5. The typical regression had N= 19298, R^2= .74, and RMSE= .263.

Table 2

The Effects of IQ and Parental Education
on Wage Levels and Education Slopes

Dependent Variable: Log Real Hourly Wage (1967 Dollars)

Explanatory Variables	Young Men							
	Equations without Family Fixed Effects[1] (Coefficients and Standard Errors Have Been Multiplied by 100)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education[2] (based on a cubic specification)	4.39	3.78	2.95	3.94	3.98	4.02	3.27	2.68
	(.409)	(.415)	(.458)	(.450)	(.435)	(.454)	(.439)	(.496)
Education × Experience	.173	.172	.174	.173	.173	.174	.168	.171
	(.032)	(.032)	(.032)	(.032)	(.032)	(.032)	(.032)	(.032)
Education × IQ	--	--	-.007	--	--	--	--	-.015
			(.013)					(.013)
Education × DADED	--	--	--	.074	--	.050	--	.054
				(.034)		(.037)		(.037)
Education × MOMED	--	--	--	--	.080	.064	--	.064
					(.036)	(.040)		(.040)
Education × EDINDEX	--	--	--	--	--	--	.083	.240
							(.079)	(.087)
IQ[3] (based on a cubic specification)	--	.274	.334	.275	.272	.273	.248	.319
		(.038)	(.044)	(.039)	(.039)	(.039)	(.039)	(.044)
DADED[2]	-.256	-.285	-.267	-.335	-.312	-.319	-.346	-.372
	(.108)	(.108)	(.108)	(.123)	(.109)	(.124)	(.109)	(.124)
MOMED[2]	.607	.553	.537	.535	.492	.477	.513	.421
	(.118)	(.118)	(.118)	(.118)	(.124)	(.126)	(.118)	(.126)
EDINDEX[4]	--	--	--	--	--	--	1.23	.986
							(.239)	(.244)

NOTES:

1. In addition to the variables reported, all regressions contain the following control variables: year dummies, experience (defined as the number of years since last enrolled in school), experience squared, number of siblings, and indicators for race, residence in an SMSA and in the South, two parents in the household when the child was 14 years old, and indicators representing missing variable reports.

2. Education is defined as highest grade completed minus 12, so its coefficient is read as the additional wage accruing to a year of education past high school. A similar interpretation holds for father's education (DADED) and mother's education (MOMED) coefficients.

3. IQ is defined as the individual's reported IQ score minus 100.

4. EDINDEX is an index of parental influence and school quality factors which predict number of years of education.

5. The typical regression had N= 19298, R^2= .29, and RMSE= .386.

Table 3

The Effects of IQ and Parental Education
on Wage Levels and Education Slopes

Dependent Variable: Log Real Hourly Wage (1967 Dollars)

Explanatory Variables	Young Women							
	Equations with Family Fixed Effects[1] (Coefficients and Standard Errors Have Been Multiplied by 100)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education[2] (based on a cubic specification)	7.78	7.48	6.58	7.00	9.44	8.57	6.78	6.53
	(.962)	(.974)	(1.13)	(1.13)	(1.15)	(1.22)	(1.01)	(1.37)
Education × Experience	-.049	-.047	-.045	-.046	-.047	-.046	-.047	-.044
	(.043)	(.043)	(.043)	(.043)	(.043)	(.043)	(.043)	(.043)
Education × IQ	--	--	-.000	--	--	--	--	-.057
			(.046)					(.050)
Education × DADED[2]	--	--	--	.116	--	-.099	--	-.115
				(.187)		(.200)		(.205)
Education × MOMED[2]	--	--	--	--	.547	.633	--	.711
					(.212)	(.226)		(.234)
Education × EDINDEX	--	--	--	--	--	--	.310	.480
							(.310)	(.344)
IQ[3] (based on a cubic specification)	--	-.284	-.276	-.298	-.331	-.336	-.316	-.288
		(.132)	(.146)	(.133)	(.133)	(.133)	(.132)	(.146)
EDINDEX[4]	--	--	--	--	--	--	2.71	2.97
							(.820)	(.832)

NOTES:

1. In addition to the variables reported, all regressions contain the following control variables: year dummies, experience (defined as the number of years since last enrolled in school), experience squared, and indicators for residence in an SMSA and in the South, two parents in the household when the child was 14 years old, and indicators representing missing variable reports.

2. Education is defined as highest grade completed minus 12, so its coefficient is read as the additional wage accruing to a year of education past high school. DADED is the average report over all sisters in the family, rather than the individual young woman's report, of father's education minus 12; mother's education (MOMED) is constructed similarly.

3. IQ is defined as the individual's reported IQ score minus 100.

4. EDINDEX is an index of parental influence and school quality factors which predict number of years of education.

5. The typical regression had N= 14320, R^2= .72, and RMSE= .263.

Table 4

The Effects of IQ and Parental Education
on Wage Levels and Education Slopes

Dependent Variable: Log Real Hourly Wage (1967 Dollars)

Explanatory Variables	Young Women							
	Equations without Family Fixed Effects[1] (Coefficients and Standard Errors Have Been Multiplied by 100)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education[2] (based on a cubic specification)	6.26	5.78	5.04	5.15	5.37	5.04	5.14	3.73
	(.502)	(.503)	(.551)	(.537)	(.523)	(.541)	(.520)	(.594)
Education × Experience	-.002	-.022	-.015	-.023	-.021	-.021	-.030	-.025
	(.043)	(.042)	(.042)	(.042)	(.042)	(.042)	(.042)	(.042)
Education × IQ	--	--	-.085	--	--	--	--	-.089
			(.015)					(.016)
Education × DADED	--	--	--	-.119	--	-.107	--	-.072
				(.042)		(.047)		(.047)
Education × MOMED	--	--	--	--	-.081	-.027	--	-.023
					(.044)	(.049)		(.050)
Education × EDINDEX	--	--	--	--	--	--	.086	.379
							(.103)	(.111)
IQ[3] (based on a cubic specification)	--	.296	.398	.302	.300	.303	.259	.368
		(.042)	(.045)	(.042)	(.042)	(.042)	(.043)	(.045)
DADED[2]	.007	-.139	-.137	.049	-.100	.028	-.212	-.104
	(.122)	(.122)	(.122)	(.134)	(.123)	(.135)	(.122)	(.135)
MOMED[2]	.307	.260	.290	.258	.344	.316	.187	.259
	(.137)	(.136)	(.136)	(.137)	(.139)	(.141)	(.137)	(.141)
EDINDEX[4]	--	--	--	--	--	--	1.64	1.54
							(.283)	(.283)

NOTES:

1. In addition to the variables reported, all regressions contain the following control variables: year dummies, experience (defined as the number of years since last enrolled in school), experience squared, number of siblings, and indicators for race, residence in an SMSA and in the South, two parents in the household when the child was 14 years old, and indicators representing missing variable reports.

2. Education is defined as highest grade completed minus 12, so its coefficient is read as the additional wage accruing to a year of education past high school. A similar interpretation holds for father's education (DADED) and mother's education (MOMED) coefficients.

3. IQ is defined as the individual's reported IQ score minus 100.

4. EDINDEX is an index of parental influence and school quality factors which predict number of years of education.

5. The typical regression had N= 14320, R^2= .24, and RMSE= .376.

Table 5

The Effects of IQ and Parental Education on Wage Levels and Experience Slopes

Dependent Variable: Log Real Hourly Wage (1967 Dollars)

Explanatory Variables	Young Men					
	Equations with Family Fixed Effects[1] (Coefficients and Standard Errors Have Been Multiplied by 100)					
	(1)	(2)	(3)	(4)	(5)	(6)
Education[2] (based on a cubic specification)	3.27	3.49	3.31	3.21	3.27	3.44
	(.834)	(.841)	(.840)	(.841)	(.843)	(.847)
Experience[3]	2.65	2.66	2.64	2.61	2.62	2.61
	(.299)	(.308)	(.305)	(.304)	(.307)	(.314)
(Experience)^2	-.071	-.070	-.072	-.071	-.072	-.071
	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Education × Experience	.117	.091	.123	.126	.127	.105
	(.028)	(.031)	(.030)	(.030)	(.031)	(.033)
Experience × IQ	--	.017	--	--	--	.018
		(.005)				(.005)
Experience × DADED[2]	--	--	-.034	--	-.028	-.033
			(.020)		(.022)	(.023)
Experience × MOMED[2]	--	--	--	-.023	-.013	-.019
				(.021)	(.024)	(.024)
IQ[4] (based on a cubic specification)	.269	.136	.272	.272	.273	.135
	(.115)	(.121)	(.115)	(.115)	(.115)	(.121)

NOTES:

1. In addition to the variables reported, all regressions contain the following control variables: year dummies, and indicators for residence in an SMSA and in the South, two parents in the household when the child was 14 years old, and indicators representing missing variable reports.

2. Education is defined as highest grade completed minus 12, so its coefficient is read as the additional wage accruing to a year of education past high school. DADED is the average report over all brothers in the family, rather than the individual young man's report, of father's education minus 12; mother's education (MOMED) is constructed similarly.

3. Experience is measured as potential experience, that is, number of years since last enrolled in school.

4. IQ is defined as the individual's reported IQ score minus 100.

5. The typical regression had N = 19298, R^2 = .74, and RMSE = .263.

Table 6

The Effects of IQ and Parental Education on Wage Levels and Experience Slopes

Dependent Variable: Log Real Hourly Wage (1967 Dollars)

Explanatory Variables	Young Men					
	Equations without Family Fixed Effects[1] (Coefficients and Standard Errors Have Been Multiplied by 100)					
	(1)	(2)	(3)	(4)	(5)	(6)
Education[2] (based on a cubic specification)	3.78	4.27	3.96	3.78	3.89	4.28
	(.415)	(.428)	(.423)	(.423)	(.426)	(.435)
Experience[3]	1.35	1.48	1.49	1.35	1.45	1.51
	(.260)	(.268)	(.267)	(.264)	(.268)	(.274)
(Experience)[2]	.002	.002	.003	.003	.004	.003
	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
Education × Experience	.172	.110	.152	.173	.160	.110
	(.032)	(.035)	(.033)	(.033)	(.034)	(.036)
Experience × IQ	--	.029	--	--	--	.028
		(.005)				(.005)
Experience × DADED	--	--	.028	--	.047	.035
			(.019)		(.021)	(.021)
Experience × MOMED	--	--	--	-.026	-.049	-.056
				(.020)	(.022)	(.022)
IQ[4] (based on a cubic specification)	.274	.039	.277	.273	.275	.043
	(.038)	(.058)	(.038)	(.038)	(.038)	(.058)
DADED[2]	-.285	-.274	-.488	-.289	-.678	-.578
	(.108)	(.108)	(.193)	(.109)	(.211)	(.212)
MOMED[2]	.553	.546	.552	.820	1.02	1.08
	(.118)	(.118)	(.118)	(.217)	(.235)	(.235)

NOTES:

1. In addition to the variables reported, all regressions contain the following control variables: year dummies, number of siblings, and indicators for race, residence in an SMSA and in the South, two parents in the household when the child was 14 years old, and indicators representing missing variable reports.

2. Education is defined as highest grade completed minus 12, so its coefficient is read as the additional wage accruing to a year of education past high school. A similar interpretation holds for fatther's education (DADED) and mother's education (MOMED).

3. Experience is measured as potential experience, that is, number of years since last enrolled in school.

4. IQ is defined as the individual's reported IQ score minus 100.

5. The typical regression had N = 19298, R^2 = .29, and RMSE = .384.

Table 7

The Effects of IQ and Parental Education on Wage Levels and Experience Slopes

Dependent Variable: Log Real Hourly Wage (1967 Dollars)

Explanatory Variables	Young Women					
	Equations with Family Fixed Effects[1] (Coefficients and Standard Errors Have Been Multiplied by 100)					
	(1)	(2)	(3)	(4)	(5)	(6)
Education[2] (based on a cubic specification)	7.48	7.31	7.63	7.60	7.66	7.47
	(.974)	(.986)	(.980)	(.983)	(.985)	(.993)
Experience[3]	.634	.509	.726	.672	.715	.593
	(.410)	(.415)	(.415)	(.416)	(.418)	(.422)
(Experience)^2	.006	.006	.007	.006	.007	.008
	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
Education × Experience	-.047	-.023	-.065	-.061	-.067	-.040
	(.043)	(.048)	(.045)	(.047)	(.047)	(.050)
Experience × IQ	--	.003	--	--	--	.001
		(.007)				(.007)
Experience × DADED[2]	--	--	.031	--	.023	.027
			(.026)		(.029)	(.030)
Experience × MOMED[2]	--	--	--	.037	.021	.019
				(.029)	(.033)	(.033)
IQ[4] (based on a cubic specification)	-.284	-.315	-.282	-.280	-.280	-.293
	(.132)	(.143)	(.132)	(.132)	(.132)	(.144)

NOTES:

1. In addition to the variables reported, all regressions contain the following control variables: year dummies, and indicators for residence in an SMSA and in the South, two parents in the household when the child was 14 years old, and indicators representing missing variable reports.

2. Education is defined as highest grade completed minus 12, so its coefficient is read as the additional wage accruing to a year of education past high school. DADED is the average report over all brothers in the family, rather than the individual young man's report, of father's education minus 12; mother's education (MOMED) is constructed similarly.

3. Experience is measured as potential experience, that is, number of years since last enrolled in school.

4. IQ is defined as the individual's reported IQ minus 100.

5. The typical regression had N = 14320, R^2 = .72, and RMSE = .263.

Table 8

The Effects of IQ and Parental Education on Wage Levels and Experience Slopes

Dependent Variable: Log Real Hourly Wage (1967 Dollars)

Explanatory Variables	Young Women					
	Equations without Family Fixed Effects[1] (Coefficients and Standard Errors Have Been Multiplied by 100)					
	(1)	(2)	(3)	(4)	(5)	(6)
Education[2] (based on a cubic specification)	5.78	5.79	5.85	5.87	5.89	5.87
	(.503)	(.521)	(.515)	(.523)	(.525)	(.536)
Experience[3]	-.640	-.733	-.588	-.615	-.579	-.684
	(.349)	(.356)	(.355)	(.354)	(.357)	(.362)
(Experience)[2]	.030	.030	.031	.030	.030	.030
	(.016)	(.016)	(.016)	(.016)	(.016)	(.016)
Education × Experience	-.022	-.021	-.029	-.032	-.034	-.029
	(.042)	(.046)	(.044)	(.045)	(.045)	(.047)
Experience × IQ	--	.012	--	--	--	.012
		(.006)				(.007)
Experience × DADED	--	--	.006	--	-.004	-.009
			(.023)		(.026)	(.027)
Experience × MOMED	--	--	--	.029	.027	.024
				(.026)	(.029)	(.029)
IQ[4] (based on a cubic specification)	.296	.175	.297	.297	.298	.178
	(.042)	(.074)	(.042)	(.042)	(.042)	(.075)
DADED[2]	-.139	-.137	-.182	-.130	-.074	-.027
	(.122)	(.122)	(.246)	(.122)	(.273)	(.276)
MOMED[2]	.260	.264	.255	-.036	-.031	.008
	(.136)	(.137)	(.137)	(.283)	(.312)	(.313)

NOTES:

1. In addition to the variables reported, all regressions contain the following control variables: year dummies, number of siblings, and indicators for race, residence in an SMSA and in the South, two parents in the household when the child was 14 years old, and indicators representing missing variable reports.

2. Education is defined as highest grade completed minus 12, so its coefficient is read as the additional wage accruing to a year of education past high school. A similar interpretation holds for father's education (DADED) and mother's education (MOMED).

3. Experience is measured as potential experience, that is, number of years since last enrolled in school.

4. IQ is defined as the individual's reported IQ score minus 100.

5. The typical regression had N = 14320, R^2 = .24, and RMSE = .377.

Table 9

The Effects of IQ and Parental Education on Wage Levels and Education Slopes

Dependent Variable: Log Real Hourly Wage (1967 Dollars)

Explanatory Variables	Young Men							
	Equations with Linear Specification of Education[1] (Coefficients and Standard Errors Have Been Multiplied by 100)							
	Without Family Fixed Effects				With Family Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education[2] (based on a linear specification)	3.86 (.295)	3.99 (.287)	3.97 (.284)	3.22 (.321)	3.26 (.670)	3.57 (.645)	3.66 (.605)	2.95 (.566)
Education × Experience	.115 (.027)	.158 (.027)	.163 (.027)	.166 (.029)	.108 (.027)	.111 (.027)	.112 (.027)	.110 (.028)
Education × IQ	.001 (.012)	--	--	--	.025 (.038)	--	--	--
Education × DADED[3]	--	.085 (.030)	--	--	--	.219 (.134)	--	--
Education × MOMED[3]	--	--	.090 (.033)	--	--	--	.408 (.157)	--
Education × EDINDEX	--	--	--	.092 (.050)	--	--	--	.082 (.158)
IQ[4] (based on a cubic specification)	.318 (.043)	.281 (.038)	.277 (.038)	.249 (.039)	.276 (.129)	.306 (.113)	.313 (.114)	.260 (.115)
DADED[2]	-.270 (.108)	-.355 (.121)	-.315 (.109)	-.347 (.109)	--	--	--	--
MOMED[2]	.546 (.118)	.538 (.118)	.485 (.123)	.514 (.118)	--	--	--	--
EDINDEX[5]	--	--	--	1.23 (.227)	--	--	--	2.35 (.706)

NOTES:

1. For a list of control variables used in each regression, see footnote 1 in Table 3 for the specifications with a family fixed effect, Table 4 for those without.

2. Education, DADED, and MOMED are defined as highest grade completed minus 12, so their coefficients are read as the additional wage accruing to a year of education past high school.

3. The equations with family fixed effects use the averaged brothers' reports of DADED and of MOMED, rather than the individual young man's corresponding reports.

4. IQ is defined as the individual's reported IQ score minus 100.
5. EDINDEX is an index of parental influence and school quality factors which predict number of years of education.
6. The typical regression without fixed effects had N= 19298, R^2= .28, and RMSE= .384. The typical regression with fixed effects had N= 19298, R^2= .74, and RMSE= .263.

Table 10

The Effects of IQ and Parental Education on Wage Levels and Education Slopes

Dependent Variable: Log Real Hourly Wage (1967 Dollars)

Explanatory Variables	Young Women							
	Equations with Linear Specification of Education[1] (Coefficients and Standard Errors Have Been Multiplied by 100)							
	Without Family Fixed Effects				With Family Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education[2] (based on a linear specification)	7.07 (.371)	6.49 (.355)	6.52 (.353)	5.46 (.398)	5.71 (.780)	5.78 (.779)	6.85 (.753)	5.20 (.724)
Education × Experience	-.152 (.035)	-.136 (.034)	-.123 (.035)	-.062 (.038)	-.051 (.043)	-.050 (.043)	-.037 (.043)	-.039 (.043)
Education × IQ	-.071 (.015)	--	--	--	-.010 (.044)	--	--	--
Education × DADED[3]	--	-.064 (.039)	--	--	--	.057 (.175)	--	--
Education × MOMED[3]	--	--	-.005 (.040)	--	--	--	.337 (.192)	--
Education × EDINDEX	--	--	--	.229 (.067)	--	--	--	.227 (.198)
IQ[4] (based on a cubic specification)	.382 (.045)	.316 (.042)	.312 (.042)	.259 (.043)	-.270 (.145)	-.300 (.132)	-.342 (.133)	-.337 (.132)
DADED[2]	-.121 (.122)	-.021 (.133)	-.121 (.123)	-.214 (.122)	--	--	--	--
MOMED[2]	.282 (.137)	.261 (.137)	.306 (.139)	.184 (.137)	--	--	--	--
EDINDEX[5]	--	--	--	1.53 (.276)	--	--	--	2.77 (.789)

NOTES:

1. For a list of control variables used in each regression, see footnote 1 in Table 3 for the specifications with a family fixed effect, Table 4 for those without.

2. Education, DADED, and MOMED are defined as highest grade completed minus 12, so their coefficients are read as the additional wage accruing to a year of education past high school.

3. The equations with family fixed effects use the averaged sisters' reports of DADED 12 and of MOMED, rather than the individual young woman's corresponding reports.

4. IQ is defined as the individual's reported IQ score minus 100.

5. EDINDEX is an index of parental influence and school quality factors which predict number of years of education.

6. The typical regression without fixed effects had N= 14320, R^2= .24, and RMSE= .378. The typical regression with fixed effects had N= 14320, R^2= .72, and RMSE= .263.

Appendix Table A1
Summary Statistics for the Young Men's and Young Women's Data Sets

	Young Men					Young Women				
Variable[1]	Mean	Sample Size	Std Dev	Min	Max	Mean	Sample Size	Std Dev	Min	Max
Log Hourly Wage Rate[2]	1.109	19298	0.457	-0.883	5.188	0.659	14320	0.432	-0.814	3.193
Highest Grade Completed	12.858	19298	2.786	0.000	18.000	12.638	14320	2.403	0.000	18.000
IQ Score	101.127	13304	15.442	50.000	158.000	102.312	9948	14.859	46.000	158.000
Father's Education	9.709	14451	3.732	0.000	18.000	9.844	10462	3.855	0.000	18.000
Mother's Education	10.143	16736	3.258	0.000	18.000	10.202	12758	3.176	0.000	18.000
Age	29.057	19298	3.784	24.000	39.000	28.262	14320	3.307	24.000	37.000
Years of Experience[3]	9.085	18877	4.988	0.000	28.000	9.441	14303	4.500	2.000	29.000
EDINDEX[4]	0.219	19298	2.124	-6.164	4.857	0.182	14320	1.766	-5.886	4.133
Number of Siblings	3.317	19164	2.595	0.000	18.000	3.593	14264	2.628	0.000	16.000
Two Parents in Household at Age 14?	0.832	19256	0.374	0.000	1.000	0.821	14319	0.383	0.000	1.000
Black?	0.230	19298	0.421	0.000	1.000	0.292	14320	0.455	0.000	1.000
Residence in South?	0.399	19297	0.490	0.000	1.000	0.427	14314	0.495	0.000	1.000
Residence in SMSA?	0.700	19297	0.458	0.000	1.000	0.719	14314	0.449	0.000	1.000

Notes:

1. Missing values are omitted from all calculations. The potential sample size is 19298 for young men, 14320 for young women.
2. Wage is measured in 1967 dollars.
3. Experience is measured as "potential experience," or number of years since last enrolled in school. For those individuals never enrolled in school or reporting zero years of education, experience equals age minus 14 years.
4. EDINDEX is an index of family background variables, school characteristics, and personal characteristics that predict years of education.

Appendix Table A2
Summary of Distribution of Observations in Young Men's and Young Women's Data Sets

Young Men's Data Set:

There are 19298 observations provided by 4138 individuals in the Young Men's data set, spanning the period from 1966 to 1981. Fifty-two percent of the young men contributed one, two, three or four observations; 27 percent contributed either five or six observations; and 21 percent contributed seven through twelve observations. The average number of observations per young man is 4.66, while the mode is five observations.

There are 3764 brother sets in the young men's data set, including 3423, or 90.9 percent, singletons, 309, or 8.2 percent, sets of two brothers, 31, or 0.8 percent, sets of three brothers, and 1 set of four brothers. The average number of observations per brother set (including singletons) is 5.13, the median and mode are both five observations. The maximum contribution of any brother set is 22 observations.

Young Women's Data Set:

There are 14320 observations provided by 3907 individuals in the Young Women's data set, spanning the period from 1968 to 1982. Fifty-three percent of the young women contributed one, two or three observations; 31 percent contributed either four or five observations; and 16 percent contributed six through eleven observations. The average number of observations per young woman is 3.66, while the mode is two observations.

There are 3571 sister sets in the young women's data set, including 3269, or 91.5 percent, singletons, 269, or 7.5 percent, sets of two sisters, 32, or 0.9 percent, sets of three sisters, and 1 set of four sisters. The average number of observations per sister set (including singletons) is 4.01, the median is four observations, and the mode is two observations. The maximum contribution of any sister set is 19 observations.

Pooled Data Set:

There are 33618 observations in the pooled data set with the distrubution of observations as given in the preceding young men's and young women's summaries.

There are 8039 brother-sister sets in the pooled data set, including 5367, or 81.7 percent singletons. There are 990 sets, or 15.1 percent, of two siblings, 178 sets, or 2.7 percent, of three siblings, 32 sets, or 0.5 percent, of four siblings, and 5 sets of six siblings.

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